



E.ON Energy Research Center



E.ON Energy Research Center Series

Dual Demand Side Management

Hassan Harb, Peter Matthes, Christoph Molitor, Ivelina Stoyanova, Henryk Wolisz, Antonello Monti, Dirk Müller

Volume 7, Issue 1



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Technical Report

Dual Demand Side Management

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1 Executive Summary

Dual Demand Side Management (2DSM) is an approach to manage the electrical and thermal energy demand at city district level. The aim is to facilitate the balancing of volatile renewable electricity generation, e.g. PV and wind turbine systems. The concept is based on exploiting the operational flexibility of heat supply systems in combination with thermal energy storage capacities in buildings. Thereby, the analysis focuses on heat supply systems like Heat Pumps (HPs), Combined Heat and Power units (CHPs) and storage heaters that are connected to the electrical grid and thus suitable for an electricity-driven operation.

The flexible operation of these units is enabled by the availability of thermal storage capacity. Therefore, the technical potential and the economic feasibility of different storage systems mainly hot water tanks and the inherent thermal mass of buildings is thoroughly investigated within the 2DSM project.

Further, the model of a city district of Bottrop was implemented to assess the potential for demand side management. This model can be set up for different configurations of the energy system, thus used in support of the development and evaluation of energy management algorithms.

This process played an integral part in the development of the City District Information Model (CDIM). CDIM is an integrated data management concept for city districts that can be used to facilitate the generation of city district simulation models. Furthermore, the CDIM concept allows for examining different possibilities in the design process of energy supply systems while considering the impact from and on neighboring houses.

Further, a co-simulation platform is developed to approach the computational challenge for simulating a city district energy system comprising several hundreds of buildings, as well as the corresponding energy supply units and hydraulic systems. The platform makes use of parallel computing features and is based on a modular architecture which allows for the flexible integration of different simulation environments.

The energy management scheme developed in 2DSM comprises a scheduling and a short-term balancing phase. The generation of schedules for the energy units is based on Mixed Integer Linear Programming (MIP). The short-term balancing is designed to react to the deviations from the intended operation plan considering the voltage level of the distribution grid.

A centralized and a decentralized scheduling strategy is investigated. The implementation of the coordination approaches is based on a Multi-agent system (MAS). The centralized approach shows a high coordination level but requires a large amount of input data which could be confronted by

privacy and scalability issues. The decentralized approach displays a lower coordination degree, however the major part of the intelligence is located locally within the dwellings. In this manner, the data privacy is maintained and the scalability is facilitated.

2 Introduction

2.1 Motivation for Demand Side Management

The transition from a fossil fuel based energy system towards a renewable and more efficient energy system, requires and is already inducing tremendous changes to the structure and the operation of the energy supply systems. This transition, since 2011 known as the 'Energiewende', is based on several national laws and regulations (e.g. EEG, EnEV, EEWärmeG, KWKG etc.) which are responsible for a strong increase of renewable electricity generation and decentralized energy resources in general during the last few years. As a result currently Germany has approximately 83 GW of installed renewable electricity generation capacity and in 2014 up to 30 % of the generated electricity is expected to be renewable [1]. In turn, many of the flexible gas driven peak power plants are replaced by the energy production from unpredictable renewable energy resources. While these changes are in general very positive, the dynamic changes in the availability of solar and wind energy make their integration in the power system difficult. Already today strong renewable generation in off peak demand phases results in local overloads of distribution grids and the requirement to curtail renewable generation. In light of the German plans to extend renewable electricity generation to 80 % by 2050, these difficulties will become a major problem and potentially a threat to the concept of 'Energiewende'. To minimize the requirement for expensive back-up generation capacities and controversial extension of the power grid, it is necessary to develop concepts for matching electricity production and consumption. Besides the required extension and innovations in energy storage systems, it is expected that Demand Side Management (DSM) will play a major role in the future energy system.

DSM is the concept of influencing the consumers' energy demand in respect to the consumed amount of energy in general and the time dependent consumption behavior, with the purpose of changing the load-shape according to the concurrent availability of electricity in the grid [2]. Modifications could be desired both in the time pattern and magnitude of the load. The concept of DSM itself is not new, one of the typical applications in the energy sector was to ensure constant operation of inflexible based load power plants. In the following some of the typical DSM methods of load-shaping are presented:

- 1 Peak clipping – reducing the peak load
- 2 Valley filling – increasing the demand during off-peak times

- 3 Load shifting – shifting load from on-peak to off-peak
- 4 Strategic conservation – reducing energy consumption in general
- 5 Strategic load growth – increasing energy consumption in general
- 6 Flexible load shape – making the load more flexible

[2], [3], [4]

The common DSM approaches in operation today are generally only static incentives to consume more or less energy during predefined time periods. Thereby, the lower night time electricity tariffs in a fixed time frame are a typical example of static Price-Based Control (PBC). However, motivated by appearing negative electricity prices on the European Energy Exchange (EEX) the industrial sector has already started to provide available flexibility to the energy market. Still, residential and commercial buildings, accounting for up to 30 % of Germany's end energy consumption (mostly thermal energy), could also provide a great amount of flexibility to balance fluctuating electricity generation. Thus, a totally new approach of energy management and control is required to ensure dynamic DSM opportunities in the building sector. Such an approach is developed and introduced within the Dual Demand Side Management (2DSM) Project.

2.2 Concept of Dual Demand Side Management

Today most of the energy consumed in residential buildings is used to cover the heat demand via combustion processes. Even if electrical heat supply systems are in place they are not dynamically controllable. If at all, they only follow static DSM signals as exemplary given by some fixed hours with a lower night time electricity tariff. Matching fluctuating renewable electricity generation with the heat demand of buildings, however, requires dynamic DSM control. Therefore, within 2DSM a concept is developed to manage the total energy demand (i.e. electrical and thermal) on city district level in a holistic way. In particular, to facilitate the balancing of excess renewable electricity generation (e.g. at times of strong wind or high Photovoltaic (PV) power generation) the dynamic control of thermal supply systems combined with thermal energy storages in buildings is part of the 2DSM concept. Thus, this concept uses renewable generated electricity for heating purposes whenever it is abundantly available. Thereby, the concept focuses on supply systems like Heat Pumps (HP), Combined Heat and Power (CHP) and storage heaters.

2.3 Approach and Methodology

In order to develop the 2DSM concept, the flexibility provided by the integration of energy storage into the system must be first analyzed. Therefore, at first the potential of different storage

technologies for that purpose has been analyzed and is presented in chapter 3. Since thermal hot water storage technology turned out to be the most efficient and already well established technology, the observed supply systems in this analysis are combined with such prevalent buffer tanks. Such storage is already being installed with any HP or CHP system, to reduce the required start-ups of these systems. In our analysis hot water tanks were dimensioned with up to 0.8m^3 to provide sufficient storage capacity. Thus, storage tanks are larger in comparison with the typically installed $0.3 - 0.5\text{m}^3$ tanks, however neither installation cost nor installation space requirements would change drastically for the chosen configurations. The inherent thermal storage capacity of a building attributable to the thermal capacity of the used construction materials was also analyzed in the preceding study. Still, extensive further analysis is required to be able to specify the available thermal capacity of different building types in changing internal and external thermal conditions. Therefore these effects were not yet taken into account for 2DSM activities.

In order to assess the potential of the 2DSM concept under most realistic conditions, a model of a city district energy system has been implemented. The model allows for simulating different configurations of the energy system and supports the development of energy management algorithm which can be tested within a simulation environment. The parameterization of the developed model has been carried out based on an existing city district in Bottrop (Section 2.4). The modeling of the individual components, as well as the approaches for the parameterization are described in detail in section 4.3. In order to enable the simulation of a city district energy system comprising several hundreds of buildings and the corresponding energy supply infrastructure a simulation platform had to be developed. The simulation platform exploits parallel computing features and enables the flexible integration of different simulators. The approach and the implementation of the simulation platform are described in section 4.4.

The 2DSM concept aims at exploiting the full available potential of thermal storage capacities on city district level to contribute consumption and generation flexibility for the electrical grid. Furthermore, as opposed to currently implemented DSM approaches, 2DSM will also account for the current condition of the local distribution grid. Thereby, the distribution grid is monitored to make sure, that frequency and voltage will be always in the requested ranges even if local renewable generation or DSM activities are stressing the grid. If necessary the 2DSM system will react and deviate from the intended operation scheme to protect the grid. Finally, based on the analysis of cooperative operation of supply systems, storage systems and electrical grid the 2DSM concept can yield indications for optimal design and refurbishment approaches for city districts.

2.4 Innovation City Bottrop

In early 2010 an industrial consortium of 70 companies, the "Ruhr Initiative Committee" and the government of North Rhine-Westphalia started a state wide contest to select a suitable city for the

implementation of an innovative climate protection model. The city of Bottrop was selected to become the model town of "InnovationCity Ruhr". The idea of the "InnovationCity Ruhr" project is to use existing structures and systems of the city and reshape it into a low-energy entity along more sustainable lines. The main declared goal for the model town is a 50 % reduction of CO₂ emissions by the year 2020 as compared to the emissions of 2010 [5].

The implemented activities are bundled in five fields of action focusing on residential and non-residential buildings, on the introduction of new energy technologies, the redesign of mobility strategies and the urban city development in general. However, while these are specific activities within the framework of "InnovationCity Bottrop", it is intended to obtain generally applicable and reproducible results that ultimately contribute in emissions reduction.

Thereby, the 2DSM project was one of the conceptual studies in the region of Bottrop. Thus, an existing city district in Bottrop was used for parameterizing the 2DSM simulation with building and electrical grid data. Furthermore, the distribution of supply system types was also performed based on the current building and supply system status within the observed area. Locations for HP or CHP installations for instance were chosen according to suitable heating demands and consistent building age. 2.1 shows the designated area of investigation for 2DSM.

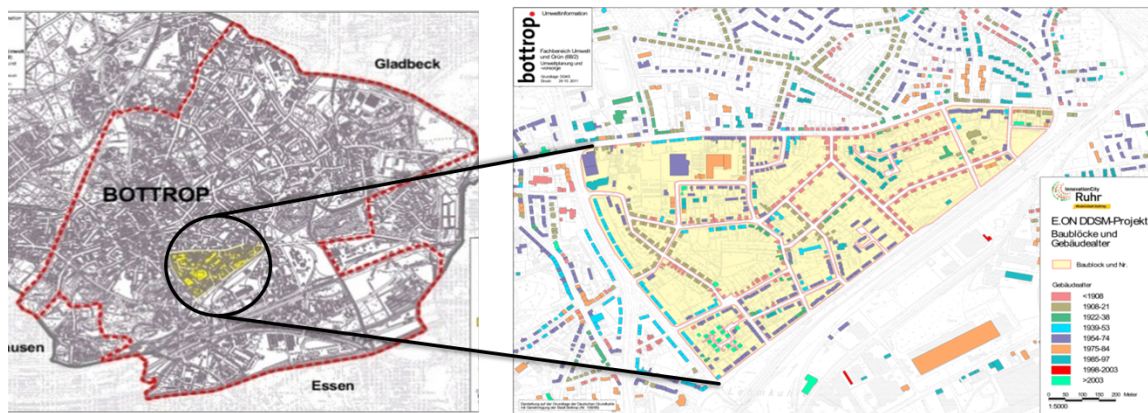


Figure 2.1: City district analyzed within 2DSM

3 Thermal Storage as Flexibility Resource for DSM

Successful implementation of DSM despite the need to fulfill the energy demands in residential buildings at any time requires flexible thermal and electrical loads. Thus, either the actual demand has to be directly shiftable without user interference or storage technologies are required to decouple electricity and heat generation and consumption. Thereby, either large centralized storage technologies or decentralized local energy buffers can be utilized. Besides of direct electricity storage technologies the idea of coupling electricity with the huge thermal demand in buildings is very promising. In addition to the huge amount of already installed night storage heating systems a growing amount of buildings is equipped with electro-thermal heating system (i. e. HP & CHP systems). Such modern installations often come along with smart meters and energy management infrastructures.

Utilizing the hot water buffer tanks usually installed with these supply systems is one of the main sources of flexibility in a residential building. However, the idea to actively manage the installed supply systems to load the inherent structural thermal capacity of the building was also analyzed within our project. Additionally, an analysis was performed comparing other existing centralized and decentralized storage technologies, in regard to their capability and efficiency in storing the energy required to cover the heating demand of an exemplary single-family house.

3.1 Analysis of the Structural Thermal Capacity of Buildings

Based on dynamic thermal simulations of different buildings and a field test within our research center it was shown that controlled activation of the thermal mass of a building has a considerable effect upon the subsequent heating demand. Results indicate that a state-of-the-art building conform to the requirements of the German energy directive (EnEV) 2009 is able to postpone heating demand by more than eight hours after a three hour phase of intense heating [6]. Older, non-insulated buildings, however, might only achieve few hours of reduced heating demand after activation of the thermal mass. Thereby, while even a regular radiator heating showed applicability to load the thermal mass, supply systems directly integrated in the buildings structure like Concrete Core Activation (CCA) allowed thermal storage even without significant indoor temperature peaks. Furthermore, it was shown that controlling the activation of thermal mass based on an exemplary signal indicating high availability of Renewable Energies (RE) might significantly increase the share of RE used for the heating purpose. In the performed CCA based field test scenario, RE

consumption was even doubled due to the signal based operation. Indeed the performed simulations indicated that in scenarios with excess renewable energy available between approximately 15 % and 40 % of the simulation time, the activation of the thermal mass allowed to double the share of consumed renewable energies. Based on this results, analysis will be extended for further building structures and DSM algorithms based on thermal storage in building mass will be developed for different supply systems. Furthermore, the comfort of residents in such dynamically changing thermal conditions will be analyzed in more detail in the future. [7]

3.2 Exemplary Results for the Field Test at our Research Center

Further analysis of the thermal mass behavior was performed in a field test at our research center. Thereby, a well monitored room was intensely heated (approximately 2.1 kW for three hours) once with the CCA and once with a radiator system. While the heating phase caused only a room temperature increase by 0.2 K for the CCA system, the radiator setup induced 3.1 K temperature increase, heating the room to possibly inconvenient 25.3 °C (figure 3.1). However, this increase of room temperature enables thermal storage in all wall surfaces and other thermal masses (e.g. furniture), which results in many thermal masses just loaded in the surface layers for the radiator system, yielding an exponential temperature decrease in the cool down phase. In turn the CCA mainly uses the capacity of the activated wall, therefore this single thermal mass which is loaded up to the deeper layers leads to a linear temperature decrease. Thus, for thermal storage in the buildings thermal mass CCA or other heat delivery systems within the building structures seem favorable, especially since they are also suitable for cooling and pre-cooling of the thermal mass. Nevertheless, radiator systems which are by far more common and will still be the typical heating system for many years to come are also suitable for thermal storage. Still, the usage of radiator systems must be thoroughly planned to take higher energy demand into account and ensure comfortable indoor climate. [8]

Nevertheless, it can be seen that both storage approaches allow more than eight hours without heating demand, if temperatures of 0.5 K below the start value are allowed. However, since the radiator system can interfere with thermal comfort expectations it would be preferable to schedule heating phases at times without occupancy. Both systems have an increased energy demand due to the strong heating period. However, the CCA system mainly loses energy to rooms adjacent to the activated ceiling while the radiator system loses heat to the ambient due to an increased temperature delta to the ambient. This results in 18 % higher energy demand for the CCA and 27 % higher energy demand for the radiator setup due to the intense heating.

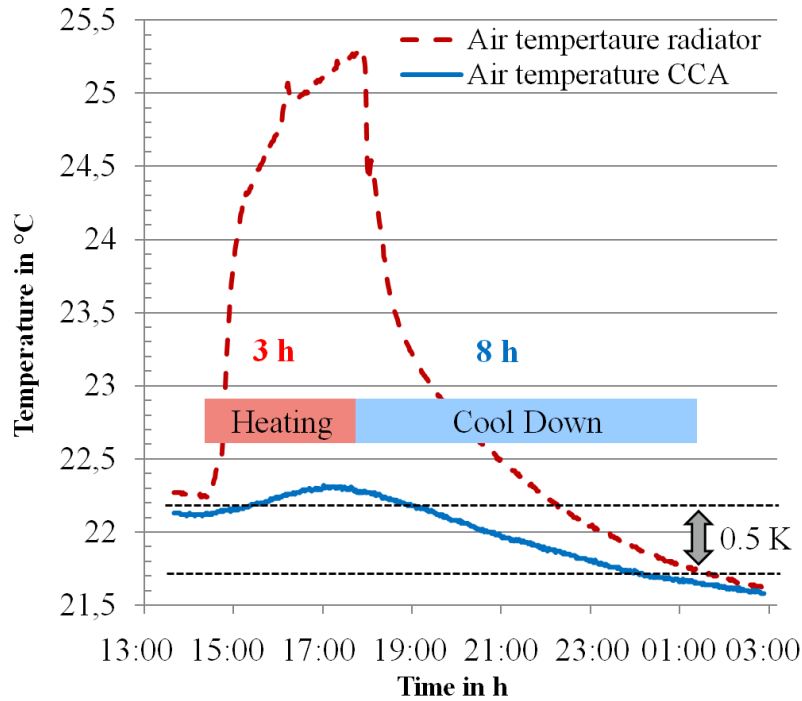


Figure 3.1: Comparison of measured overheating and cool down phases

3.3 Comparison of Thermal Storages With Other Storage Technologies

To enable the comparison of storage technologies that are highly different in size, location and operation mechanism, specified usage scenarios are created. These scenarios include a fixed exemplary use case for the energy storage demand, which is combined with two different electricity market pricing scenarios. It is generally assumed, that due to a growing wind and PV share in gross electricity production, the electricity exchange market price will predominantly depend on the actual availability of renewable generation in the future [9]. Thus, electricity prices will be low during times with strong wind or high insolation as renewable energies have negligible marginal generation costs [10] [11]. This will be an incentive to use electricity for domestic space heating. However, since peak times in heat demand will remain unchanged, energy storage systems must be employed to match overproduction of electricity and residential heat demand. Such storage can be either centralized and provide services for end consumers, or decentralized storage is used allowing end-users to participate in domestic DSM activities. As a use case, this analysis focuses on the space heating energy demand for one side of a typical modern semidetached house built in the year 2004. The observed building is supplied by a heat pump system which, as the house itself, was modeled and dynamically simulated in Modelica / Dymola. Within the scope of this analysis the storage technologies presented in Table 3.1 are analyzed. Only technologies were chosen, which are already available or at least in experimental stadium with good chances for commercialization

Table 3.1: Energy storage technologies compared within this analysis

Large-scale, centralized storages	Advanced-Adiabatic and diabatic Compressed Air Energy Storage (AA-CAES and CAES) Power-to-Gas storage technology (P2G) Pumped Hydroelectric Storage (PHS) Natrium-Sulfur Battery (NaS) Vanadium Redox Battery (VRB)
Decentralized battery storages	Lithium-Ion and lead-acid battery
Decentralized thermal storages	Sensible Heat Storage (SHS) (hot water tank)

and profitability within the upcoming decade. These storage technologies are benchmarked based on the Levelized Cost of Energy (LCOE) method. Since this approach combines technical as well as economic factors of a system, it is suitable [1] for the comparison of different energy generation and storage technologies. [12]

3.4 Approach of Storage Comparison

Investment costs used for this analysis are based on an extensive literature research. Since a very wide range of costs was found, values deviating the most were neglected and an arithmetic mean average of the remaining data base was calculated. Thereby, the associated median values differed not more than 5 % from the mean values. Depending on the typically used description for a given technology, either power or capacity costs were used in this analysis. Installation costs of hot water tanks cannot be easily associated with a given power or capacity, since the storage parameters depend on operating conditions like the temperature spread. Therefore, the costs c of the thermal storage were calculated according to formula 3.1, which resulted from an extensive analysis of existing thermal storage installations [13]. Thereby, according to [14] a correction factor of 2.3 is used to account for higher quality material and better workmanship as typically found in residential installations, in contrast to industrial storage tanks. Furthermore, additional installation such as piping and storage control, which increase the water tanks' investment costs, are accounted for by the value of 1.2 at the end of the formula. The water volume V is given in liter.

$$c = 18.179 \cdot V[l]^{0.6347} \cdot 2.3 \cdot 1.2 \quad (3.1)$$

Literature information about the technical specifications of the analyzed energy storage technologies deviated distinctly less than the cost data. Yet, for premature technologies, such as AA-CAES and P2G plants, there is still uncertainty for factors like efficiency or life span. In such cases the extreme values were also omitted and an average was calculated. Table 3.2 gives an overview of the

most important input factors used in this analysis.

Table 3.2: Values used in LCOE calculation

Technology	Today [€/kW]	2020 [€/kWh]	Today [€/kW]	2020 [€/kWh]	Efficiency	Life span [a]
PHS	1,290	—	1,290	—	80 %	50
CAES	695	—	695	—	150 %	50
AA-CAES	—	—	840	—	70 %	50
P2G	2,300	—	1,600	—	36 %	30
NaS	2,005	—	1,850	—	80 %	10
VRFB	3,230	—	2,200	—	80 %	36
Li-Ion	—	835	—	300	95 %	8
Lead Acid	—	230	—	200	80 %	6
SHS	<i>Equation 3.1 is used for a 1460l tank</i>				85 %	20
Gas Turbine	460	—	460	—	38 %	50

The dimensions used for centralized and decentralized storage differ. Centralized systems are sized according to the scale most suitable for the given technology and typically found in existing projects. The decentralized systems are dimensioned to cover 90 % of the average daily heating demand of the exemplary building. Thereby, the required battery capacity is just one third of the thermal storage capacity due to the underlying heat pump COP, which has an average of 3 in the simulated heating period.

Two scenarios, both having two different electricity prices for centralized and decentralized storage systems, are used in the evaluation of this analysis. The average intraday price on the power exchange market in 2013 was about 4.1 ¢/kWh [15]. Since the storage systems are being charged in times with significant renewable energy generation, the power exchange market price in the charging phases is assumed to be 2 ¢/kWh for both scenarios. However, a large share of the electricity price in Germany consists of taxes and levies [16]. Included is the “EEG” and “KWK” levy, which are used to subsidize direct renewable electricity generation, CHP plants, bio mass plants and other systems supporting the transition of the electricity market [17].

Scenario A takes these levies into account resulting in a relatively high electricity price, as compared to the actual generation costs. Thereby, according to the current price structure a regular household would have to pay 25.4 ¢/kWh, the operator of a centralized storage plant 8.7 ¢/kWh for the stored electricity. The reasons for the deviation are different schemes of taxes and levies for large-scale electricity consumers in Germany. Thus, scenario A roughly represents the current status on the German electricity market, solely with the adaption that end-consumers can buy electricity at the dynamic price of the energy exchange market. However, the legal framework for the electricity levies is heavily discussed at the moment and changes are expected. One possible option would be to exempt consumer supporting the consumption of excess renewable electricity

from the EEG levy [18]. Therefore in scenario B, EEG levies are neglected and only costs for transport and measurement as well as sales tax is added on top of the power exchange market price for electricity. In result, the household price sinks to approximately 14.8 ¢/kWh. For large-scale storage systems, it is taken into account that the government is currently discussing to relieve storage system operators of several levies [19] leading to a price of 4.2 ¢/kWh.

In both scenarios the operator of any central storage adds a 9 % profit margin upon his costs. Furthermore, according to current market structure, the electricity sold by the storage operator is again subject to the governmental taxes and levies (17.1 ¢/kWh) before the final household prices evolve, which can be compared with prices used for the decentralized storage technologies. The interest rate for the investments is set to 6 %. The current natural gas price of 4.8 ¢/kWh (incl. sales tax) [20] for commercial customers is used throughout the analysis, as prices are not expected to rise considerably in the near future [1].

3.5 Results of Storage Comparison

The results show a large gap between the technical costs of storing energy and the actual full costs of stored electricity. Many storage technologies would be profitable as of today, if stored excess renewable energy could be sourced and sold without fees, taxes and levies 3.2. However, such a scenario cannot be expected in the near future. Nevertheless, even with all current electricity duties and levies, many storage technologies can be profitable if all the market participants are given the opportunity to benefit from dynamic electricity generation price 3.3. If levies supporting renewable energies would be suspended for customers sourcing excess renewable energy, a wide portfolio of storage technologies will enable storing and supplying electricity with costs lower than a typical peak-load generator gas turbine 3.4.

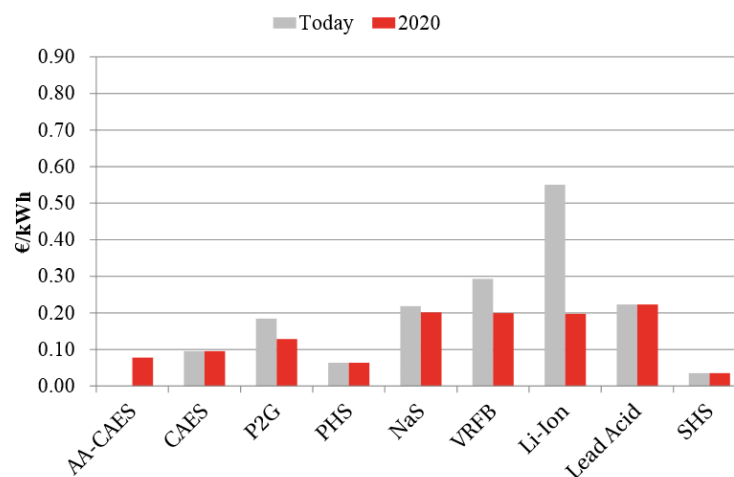
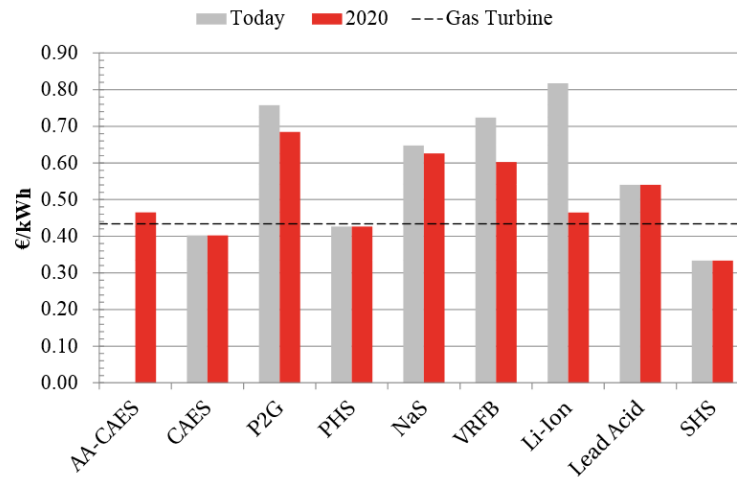
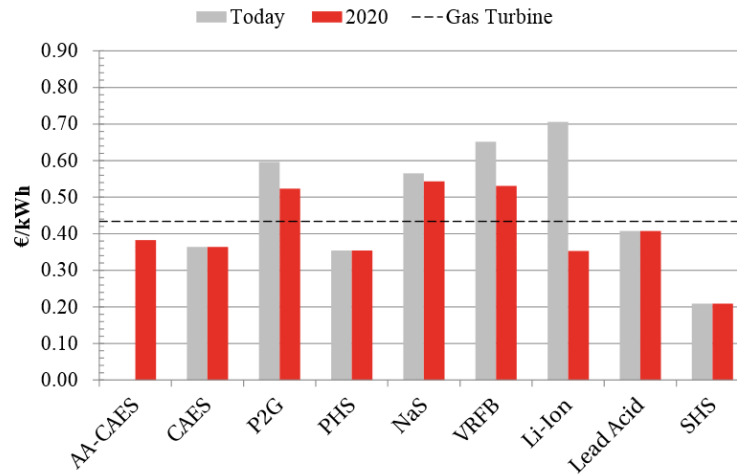


Figure 3.2: Cost of Storage

**Figure 3.3:** Full costs for scenario A**Figure 3.4:** Full costs for scenario B

PHS, CAES and AA-CAES are the most cost efficient centralized storage technologies, still their potential for the future differs. PHS is a mature, well developed technology, with established and long optimized main components, i.e. the water turbines [21]. However, due to the fact that most suitable geological locations in Germany are already in use, the potential for new projects is limited [22]. CAES and the expected technical development towards AA-CAES prove to be a viable option in storing electricity as well, though it has similar limitations as it also relies on geological formations for storage. Nevertheless, since only 2 CAES plants exist so far (Huntorf & McIntosh), suitable locations are not limited yet and globally many new projects are currently in the planning phase [23] [24].

Except for lead acid batteries, technical development of the analyzed battery storages is not yet finished. Hence, current costs cannot compete with the other observed technologies, though results

display substantial cost reductions in the future. Especially for lithium-ion batteries, which play a major role in the e-mobility, massive decreases of installation costs are expected. Although lead acid is a mature technology, it cannot keep up with the costs of other batteries. In addition, it has several technical limitations like a low depth of discharge and life span [25]. The evaluation of the Power-to-Gas technology within the scope of this analysis is difficult, as high uncertainty regarding technical maturity, installation costs, efficiency and life span exists. Though, at least until the year 2020 P2G will stay in the experimental phase, thus not being a profitable solution for electricity storage within the given use-case.

Finally, decentralized SHS features the lowest costs of all storage technologies. This might have been expected, since it is usually recommended to store energy with the technology associated to the final energy demand, which in this case is the heat supply. However, the huge cost advantage towards the other storage technologies, which is in scenarios A and B approx. 10 ¢/kWh, highlights the relevance of thermal storage for the dissemination of electricity driven heating systems. If the costs of energy stored by SHS in scenario B (21 ¢/kWh) is compared to the current regular electricity price in Germany (approx. 29 ¢/kWh), the energy costs of our use case house (yearly heating electricity demand of 4710 kWh) could be reduced by up to 377 € per year (formula 3.2). This extent of possible savings would justify the required initial investments in smart metering and energy management technologies.

$$4710 \text{ kWh}_{el}/a \cdot 0.08 \text{ €}_{savings}/\text{kWh}_{el} = 377 \text{ €/a} \quad (3.2)$$

Yet, especially when comparing expected storage costs to the electricity generation costs of the gas turbine, it can be expected that the predicted dissemination of electricity based supply systems will go hand in hand with an steep increase in storage capacities, enabling the cost efficient match of energy demand and electricity supply. This analysis has shown, that a fundamental and profitable contribution for the required energy storage capacities can be made by smart control of conventional sensible hot water storage tanks. Based on this preceding analysis the further development of an innovative DSM concept will be based on the flexibility deployed to residential buildings through thermal storage technologies.

4 Modeling and Simulation of City District Energy Systems

4.1 Introduction to Modeling of City District Energy Systems

In order to investigate novel DSM algorithms in the context of urban energy systems, it is required to simulate the urban energy system holistically so that the interaction between algorithms and the model of the physical systems is represented accurately. In the case of DSM algorithms for residential buildings in an urban area, this means that the individual building energy systems (BESs) as well as the interconnecting energy supply systems, e. g. like electrical grid or gas network, have to be modeled and simulated. Furthermore, the control algorithms at different levels have to be incorporated: on one hand the control algorithms at the application level, e. g. the internal control system of an individual BES, on the other hand, the system control level which is responsible to steer a larger group of BESs.

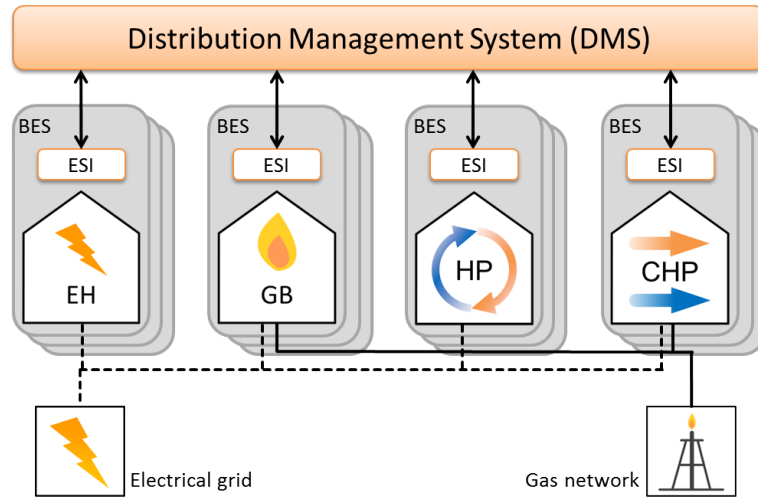


Figure 4.1: Schematic of a sample city district energy system

In this work, a city district energy system is considered as a system comprising BESs, energy supply networks as well as a higher level control system, here referred to as Distribution Management System (DMS). In such a system as schematically shown in Figure 4.1, each BES is equipped with a heating system (HS), like gas boiler (GB), HP, CHP or electrical heater (EH). The configuration of the HS can be monovalent or bivalent. In case of a monovalent configuration, the BES is equipped with a single heating device providing all the thermal power. In case of a bivalent configuration, typical for electro-thermal HS like HP or CHP, the HSs are equipped with an additional heater like

EH or GB. Thus, the nominal power of the main heater can be smaller while the additional heater serves as backup when needed. Bivalent systems according to this definition often require two different energy sources like electricity and gas for example. Furthermore, every BES is equipped with a so called Energy Service Interface (ESI) which provides an interface for external information and control signals from the DMS. Within the system control level for example, a Distribution Management System (DMS) could be implemented which determines the schedules for the electro-thermal HSs. The individual BESs are connected physically through energy supply networks and virtually through the control actions determined by the DMS as shown in Figure 4.1. Thus, control actions of the DMS executed in the individual BESs impact also the state of the supply networks and thus the neighbored BES. In order to be able to represent those effects, it is important to simulate the system holistically. The requirements regarding modeling and simulation of the individual functional sub systems, here BESs, energy supply networks and system level control, are given the following sections.

4.1.1 Building Energy Systems

Regarding the BESs, it is necessary to perform a dynamic simulation of the BES comprising the building envelope and its interaction with the ambient conditions and user behavior as well as the energy supply system. This simulation provides information like the actual indoor temperature and its variations which are important information for a possible control algorithm. A dynamic simulation of the building envelope is required as control algorithms might exploit the thermal inertia of the building and the HS as well as the tolerated lower temperature due to absence of the inhabitants. The internal thermal energy supply system will be modeled including heat generator, thermal energy storage and heat delivery system as it imposes constraints on possible control algorithms.

Regarding the electro-thermal systems, the startup behavior and the minimum shut-off-periods have to be represented by the models, which means that the dynamic BES models have to incorporate application level control. Furthermore, the efficiency of some electro-thermal systems, e. g. air-to-water heat pump, depend strongly on the ambient temperature but also the internal flow and return temperature which again depends on the heat delivery system and actual state of the energy storage. Thus, it is required that also the thermal storage tank is represented in sufficient detail.

The behavior of the inhabitants and the resulting electrical demand of domestic appliances has also to be represented in the model as electrical demand leads to waste heat and has an impact on the indoor temperature. Also, control algorithms might adjust the operation of the heating system to the actual internal electrical demand.

4.1.2 Energy Supply Networks

The energy supply networks supplying the individual BES, have also to be represented in the system model. This becomes necessary as the purpose of the control algorithms which should be investigated on the presented platform do not only consider internal conditions of the BES but also external conditions like the state of the supplying networks. As the individual BES are coupled through those networks and the algorithms consider the actual state of the networks, the simulation of the networks has to be executed on-line. That means a separate simulation of the BES and a subsequent simulation of the impact of the operation of the BESs on the networks does not provide sufficient information. The required information could be for example the voltage at certain nodes in the grid or the loading of the transformers or lines. However, as the purpose of this work is to investigate system level energy management algorithms, a steady state representation of the energy supply systems is sufficient, neglecting the dynamic behavior.

4.1.3 System Control

As mentioned before, the purpose of the simulation platform is to implement and test various energy management and control algorithms for city district energy systems. Thus, the simulation platform has to provide interfaces to include those algorithms. Furthermore, the system control or higher level control algorithms might follow different philosophies, e.g. centralized versus decentralized architectures, thus the simulation platform has to provide the necessary flexibility to implement various types of system level control. In order to enable a fast implementation of various control algorithms, an interface to a widely known and used fast prototyping platform like Matlab / Simulink is favorable.

4.2 Data Requirements for Modeling of City District Energy Systems

In order to build a meaningful reference scenario, a real city district as part of the city Bottrop has been modeled. As mentioned in section 2.4, Bottrop as the InnovationCity Ruhr, serves as a showcase and demonstration field for a variety of new technologies and concepts. Thus, the support of the city council of Bottrop helped to collect the required data for the modeling of the city district selected for the here presented project. The following sections describe the different data requirements as well as the sources which have been used or have been available to gather the data.

4.2.1 Building Age and Construction

As introduced in section 4.1.1, a dynamic simulation of the BES is required. Determining the energy losses of the buildings is a central point in those simulations. It must resemble the actual

demand to correctly predict the supply system behavior and its energy demand. If the supply system uses electrical energy to operate the heating devices like heat pumps or storage heaters¹ it will have a direct impact on the electrical grid. Therefore, the modeling of the thermal building behavior will use information about the construction of the building envelope like walls, roofs and windows which determine the transmission and radiation heat losses [26].

The city district, used as analysis of this project, is mainly a residential area with single and multi family dwellings. Only a few buildings are commercially used. The building stock's ages range from very young houses of ten years to others with more than 100 years. See the map of the city district in figure 4.2. The largest number of houses is built before 1974. Only a few buildings are new constructions or have undergone a refurbishment process. Therefore, most buildings will need an energy performance improvement in the next years including envelop insulation and update of the energy systems. This offers an opportunity to install smart grid ready components.

In most cases the buildings have double glazed windows and the facades are in its original state. Roofs have been refurbished with insulation in many cases but often the original state can be found as well. In general the need for refurbishment is medium to high in this area. *Innovation City Ruhr* estimates the potential for CO₂ reduction in the area to be 38 % relative to the current state. In total, an energy reduction of about 1 400 000 kWh/a can be assumed if a current level of refurbishment quality would be used.

According to the building age its construction will have a specific energy transmission resistance. This depends on the thickness and the material of the building envelope. Usually, old buildings will transmit more energy than newer ones. To parameterize the simulation models, information on the construction details must be available. This detailed data has only been present for a few houses. Therefore, the remaining stock of buildings had to be parameterized according to average construction data of houses in Germany. Data is available for different age categories for example in [27]. Figure 4.3 shows the average energy demand of European buildings per square meter over year of construction based on the analysis of Dr. Richner [28]. Very old buildings usually have thicker walls than newer constructions and hence the energy transmission will decrease. Beginning around 1975 higher insulation standards were used for new buildings which also caused a decline in energy consumption. A small set of buildings from the district in Bottrop is shown in this graphic as red dots to visualize the possible spread.

The parameterization of the buildings for the simulation platform is partly based on survey data from the district. House owners have been asked for information about the building construction and the heating supply systems. In many cases the people did not want to participate in the survey or had no idea about the specific information that was asked. Therefore, parameters for a large part of the buildings had to be gathered from available sources like the Innovation City Manage-

¹Definition from Wikipedia: "A storage heater or heat bank (Australia) is an electrical heater which stores thermal energy during the evening, or at night when base load electricity is available at lower cost, and releases the heat during the day as required."

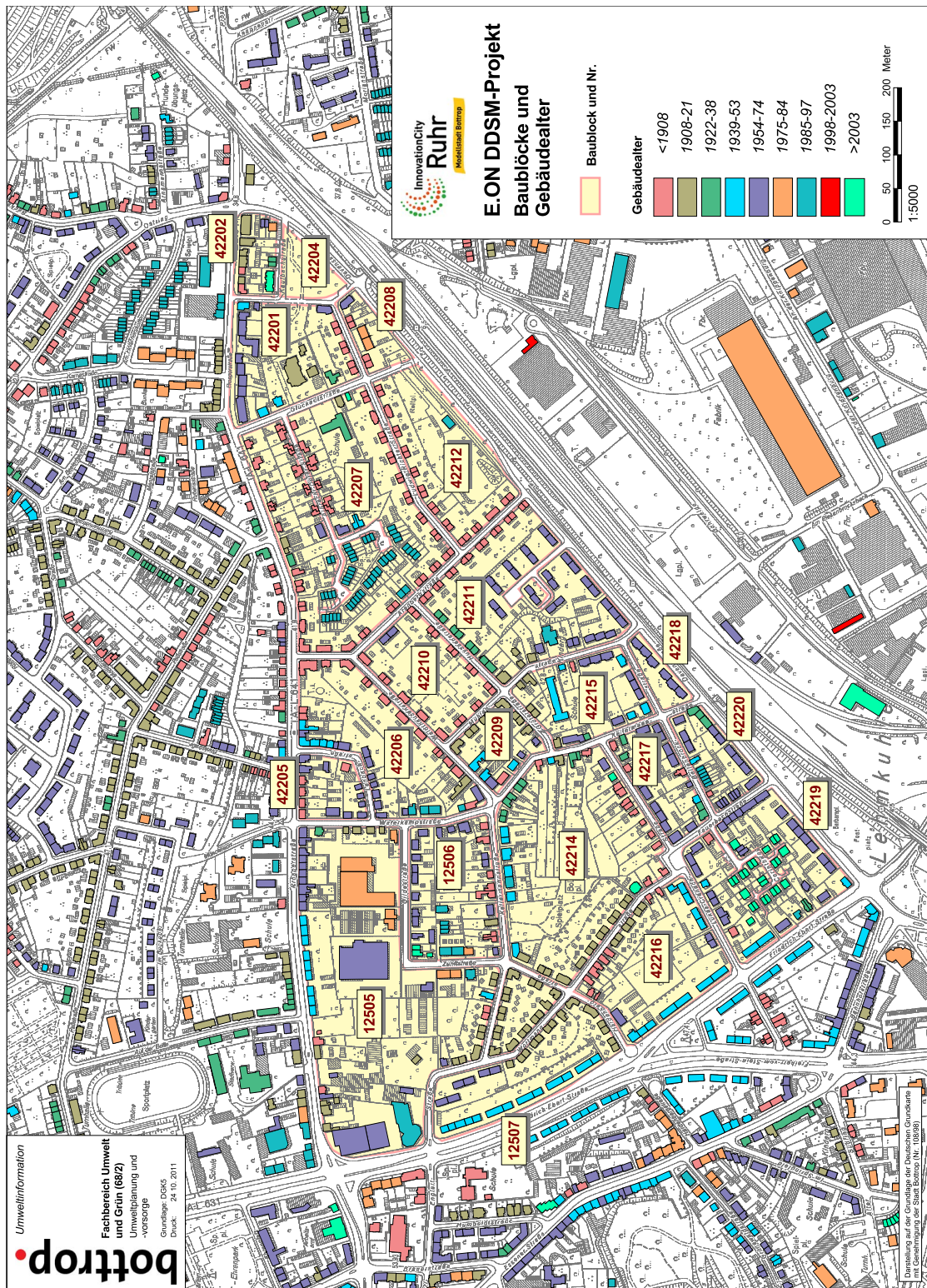


Figure 4.2: Building age in the city district (source: *Innovation City Rhur*)

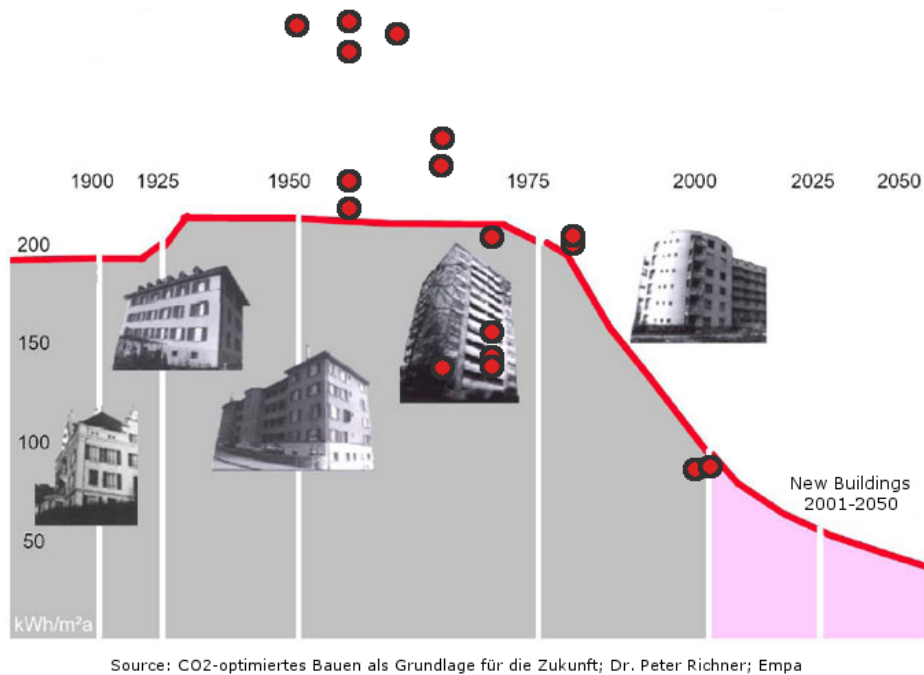


Figure 4.3: Building energy demand as a function of construction year. The dots represent a few buildings of the city district in Bottrop. (Source: Dr. Peter Richner, EMPA, Switzerland)

ment GmbH, the geo information system for Bottrop [29], photographs from the building facades, Google Maps™ and Bing™ Maps.

From the geometry of the building envelope, the number and size of windows and the building age one can assume the construction of the walls, ceilings, roof and ground slab of a house. The insulation of exterior walls can be assumed from building age or time of renovation as well as from the appearance of the walls. For a large part of the buildings thermographic pictures have been taken in wintertime, which show the surface temperatures of those buildings. Especially in comparison to other buildings, the quality of the insulation can be assessed from the pictures. All this information will be transformed into a set of parameters for each house that describes its thermal characteristics. Occupancy behavior will be generated randomly for a given number of occupants for a house.

4.2.2 Heating Systems

In Germany most energy conversion systems in residential buildings are heating units. Air conditioning can hardly be found, however, ventilation is becoming more common in young houses as a measure to ensure sufficient air exchange in ever more tight building facades.

Heating systems in Germany are in general water based using fossil fuels. Those systems include a heater device (generator), a circulation pump (distribution) and radiators in the rooms (delivery).

Often the system includes a hot water storage tank to reduce frequent switching of the heater. Heat delivery to the rooms is commonly done with radiators. They transport energy by convection and radiation. Thermostatic valves automatically control the mass flow rate through the radiators to adjust the heat output in order to keep the room temperature at a designated value. Newer homes increasingly use floor heating for increased thermal comfort at lower medium temperatures. Low supply temperatures will increase the efficiency of HP systems.

For the concept of 2DSM switchable electrical loads are interesting components for the electrical network, gas fired generators for the gas network. Large electrical loads/generators in homes are heat generation systems (CHP, HP, storage heaters) and CHP systems and boilers are gas consumers. Therefore, it is interesting to have a look at the distribution of heating systems in Germany.

Boiler systems which burn gas, oil or wood are the most common. Newer systems will be more energy efficient as they can use heat from the exhaust gas (low temperature boiler). Some systems additionally use the condensing heat of water vapor in the exhaust gas and therefore achieve very high efficiencies (95 % – 99 %).

Common heating systems that use electrical energy are storage heaters and HPs. Due to the higher annual energy consumption in comparison to other domestic appliances, e.g. washing machines or coffee machines, they offer a great potential to be used for DSM as energy sinks. Traditionally, storage heaters charge the thermal mass during night time when the demand for electrical energy is low. This charging strategy helped to use base load plants most efficiently. However, the charging strategies could be adapted in order to fulfill the flexibility needs of the future electrical energy supply systems with a higher share of fluctuating generation. As electricity is converted directly into heat the operational costs are rather high for these systems. In contrast to boiler systems, the process of HPs is much more efficient. HPs transport heat from a source like outside air or ground water to a heat sink - the house heating system - by using only a small amount of electrical energy to transport a larger quantity of thermal energy. However, in comparison to boiler systems HPs are relatively new on the market and therefore not so wide spread.

An alternative for a separate HS in each individual building, the thermal demand of the buildings could be covered by district heating systems. In Germany, district heating systems are very common in larger cities. Hot water is distributed in the city district via pipe networks to heat the buildings. Waste heat from industrial processes or waste incineration is often used.

The distribution of those heat generating systems in Germany is estimated by the Federal Ministry for the Environment, Nature Conservation, Building and Nuclear Safety (BMU): 79 % of the heating energy comes from gas and oil, 12,6 % is district heating and 6 % electrical energy in 2009 [30]. More than 450 000 gas fired heaters are sold per year in comparison to 120 000 oil and 40 000 biomass fired devices. Approximately 60 000 electrical HPs are sold each year. According to the BDH [31] gas and oil fired low temperature boilers make up about 90 % of existing heaters in the EU. Only 10 % is gas or oil condensing boilers. Approximately 1 % of the heaters are HP systems.

In recent years very small combined heat and power plants (μ CHP) are coming to the market with a strong acceleration observable [32]. However, the absolute numbers are still small. In the EU currently less than 0.1 % are combined heat and power systems (mini CHP, which are larger systems than the μ CHP) [31]. For Germany the number of approved CHP systems has risen to about 6 000 plants in 2013 [33].

The number of manageable electric loads that can be used for DSM is still small in comparison to the fossil fuel powered systems. However, constant renewal of the old system park is necessary to comply with legal requirements and increase system efficiency to limit energy costs in the long run.

The energy efficiency of the existing building stock can be improved by a number of different measures. Reducing the heat losses by better insulation and air tightness of the building is widely used. Upgrading the energy supply systems in order to use more efficient hardware is another approach. Both measures can and should be combined if possible. Lower energy losses of the building will allow using heat delivery systems with a smaller specific heat transfer rate like floor or wall heating systems. These can use lower flow temperatures and therefore increase the efficiency of the heat generators. At the same time they also improve thermal comfort for the occupant as radiation heat is often perceived more comfortable than convective heat.

In the city district in Bottrop the thermal supply systems have the need for refurbishment like the building envelope in many cases. According to EnEV 2014 [34] 30 year old gas or oil boiler systems must be replaced with state-of-the-art heaters until 2015. In contrast to the average distribution of HSs in Germany the city quarter in Bottrop uses much district heating (27 %) and only 10 % gas boilers. The rest is oil and other fossil fuels as well as numerous storage heater installations. Storage heaters can easily be adapted for use in DSM concepts.

On the simulation platform each house will have its own heat supply system. Currently models for non-electrical heat generators, HP, CHP and storage heaters are implemented. They are combined with a radiator delivery system with thermostatic valves and a thermal storage tank where applicable. The models for the supply systems will be selected and parameterized based on the scenario that will be simulated with the platform. A house will be assigned a specific supply system type according to the scenario. The size of the system will be automatically determined by the design heat power of that building. These systems can be operated stand alone or by an external signal coming from a 2DSM algorithm.

4.2.3 Representation of Occupancy Behavior and Electrical Demand of BES

As mentioned in section 4.1.1, the behavior of the occupants of a BES has an important impact on the operation of the system. Several investigations showed that the thermal energy requirements and the actual thermal load consumption can differ greatly, mainly due to the behavior of occupants and their thermal comfort standards. This mainly reflects in their heating and ventilation

patterns. Moreover, the type and consumption profiles of appliances and lights represent an significant thermal internal gains in houses. Furthermore, the analysis of energy management algorithms under realistic conditions requires to represent the electrical demand of appliances within the BESs in the simulations. The representation of the electrical demand as standard load profile (SLP) as commonly done is not sufficient as the SLP is an average profile which is only valid for an aggregation of several thousands of households. High resolution data which could be provided by smart meters would allow a realistic representation of the actual electrical power consumption. However, detailed information about the occupancy behavior regarding the impact on the thermal or electrical consumption is difficult to acquire and is typically unavailable due to concerns and regulations regarding data privacy. Furthermore, smart meter which could provide this data to a certain extend are not yet widely available.

Thus, the generation of artificial time series representing the power consumption out of statistical data is a feasible approach. We adopted the approach of the excel-tool developed by Richardson [35]. This tool uses available statistical time of use data in households to generate a user occupancy profile with a temporal resolution of ten minutes. Then, the tool assigns to a specific household a set of appliances according to statistics providing the probability for typical appliances. Afterwards, the tool determines the runtime of the assigned appliances considering the occupancy profiles which have been determined as described in 4.2.3. As a last step the time series of the power consumptions of the individual appliances are aggregated to determine the overall power consumption of the households. The resolution of the resulting time series representing the electrical demand is one minute.

The core application of this generator is translated to python and extended to generate time series for a period of one year and to generate aggregated time series for multi-family houses. Here, individual time series for each household in the multi-family house have summed up. The time series representing the electrical demand are then embedded in the thermal house model as waste heat. Moreover, the occupation profile is used as basis for generating the ventilation profile and thereby the heat transmission losses.

Figure 4.4 shows an example of an occupancy profile and the related time series of the electrical power consumption. It can be seen that there is a correlation between active occupants and the electrical power consumption. Thus, the time series' representing the occupant activity and the electrical power consumption are suitable to represent the occupant behavior consistently from the point of view of the thermal and electrical energy demand.

4.2.4 Electrical Grid

The data requirements for the modeling of the electrical grid can vary depending on the focus of the electrical simulation and the purpose of the models. For example, for industrial areas usually more data is available due to the proprietorship for a major part of the infrastructures and to the

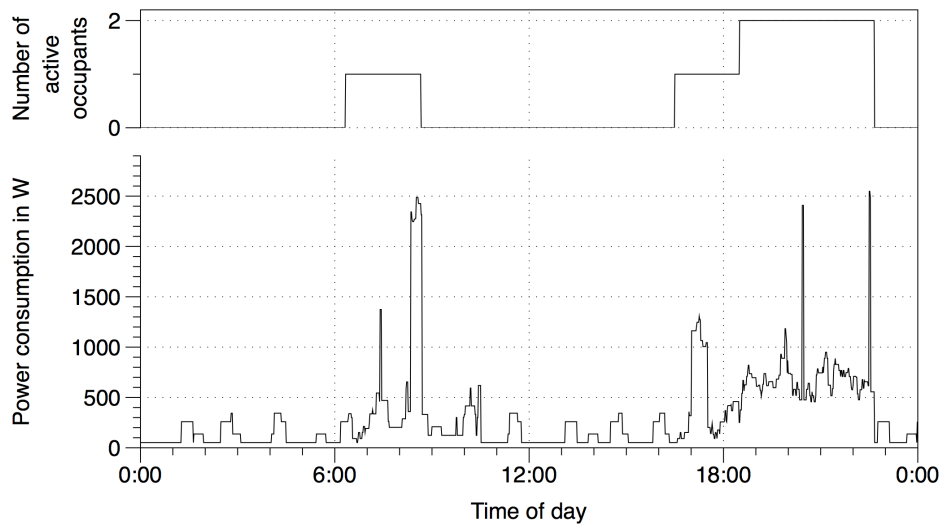


Figure 4.4: Example of occupancy profile and related time series of electrical power consumption

fixed operation schedules and close monitoring of processes. Grids in industrial areas have to be modeled at a higher level of detail due to the high energy demand and, therefore, the more critical grid operation in these areas.

In the first step of the development of 2DSM, the data requirements for the grid modeling for both residential and industrial areas have been defined (see 4.1). The data requirements are listed in categories for the advanced and minimal input data. The minimal input data regard mainly the grid infrastructure and the parameters of the critical grid equipment such as cables and transformers. The minimal input data requirements form the set of basic requirements to model a realistic grid in order to investigate the effects of control algorithms or alternative equipment on the grid. The advanced input data requirements contain further specific data which enable a more detailed grid modeling, such as the location and conventional operation mode of switches. The set of advanced data is necessary for the design of installation plans in case of intended realization in the area.

The characteristics of the project area of 2DSM and the grid modeling in particular are introduced in Models of City District Energy System Components section Electrical Grid.

4.2.5 Weather Data

For energy performance simulation generic weather data is often used. For Germany the Deutsche Wetterdienst (DWD) provides respective data called Test Reference Years (TRY)² [36]. This data is based on actual weather recordings over a long time to represent average and extreme weather conditions that can be expected in a specific region inside Germany. The effect of temperature in-

²Dataset with software tool available under: http://www.bbsr-energieeinsparung.de/BBSR/DE/FP/ZB/Auftragsforschung/5EnergieKlimaBauen/2008/Testreferenzjahre/TRY2011_Datensatz1_1.zip

Table 4.1: Minimal and detailed data requirements for the modeling of the electrical grid in residential and industrial areas

Level	Minimal input data requirements	Advanced input data requirements
Residential	Topology of the electrical grid for low and medium voltage	Junction boxes Switches Exact parameters of any other installed grid equipment
	Substation parameters: type, short circuit voltage, nominal capacity	Switching status, conventional operation configuration
	Cables: type, width, lay-out (underground or overhead), lay-out plan	Time resolved electricity consumption for each residential and industrial customer
	Generation units	Load profile heat pumps
	Electricity consumption	Exact data on the availability, placement and operation parameters of equipment and storage
	Heating system	CHPs (generation profile)
	CHPs: nominal capacity, branch connection PVs: nominal capacity DC and AC, branch connection	PVs (orientation, deviation, generation profile)
Industrial (additionally)	Larger energy consumption units	Re-usable waste products such as heat or cold
	Maximum power rating of connection	
	Load curve	

crease in a city is also considered. This data is given in one hour steps. Whilst taking into account the weather recordings of many years the data set will also resemble normal weather changes during a day, week and season as a basis for reliable predictions for the energy performance of buildings. This data is comparable to the Typical Meteorological Year (TMY) by the National Climatic Data Center in the USA.

In figure 4.5 the histogram for air temperature of the used TRY is displayed.

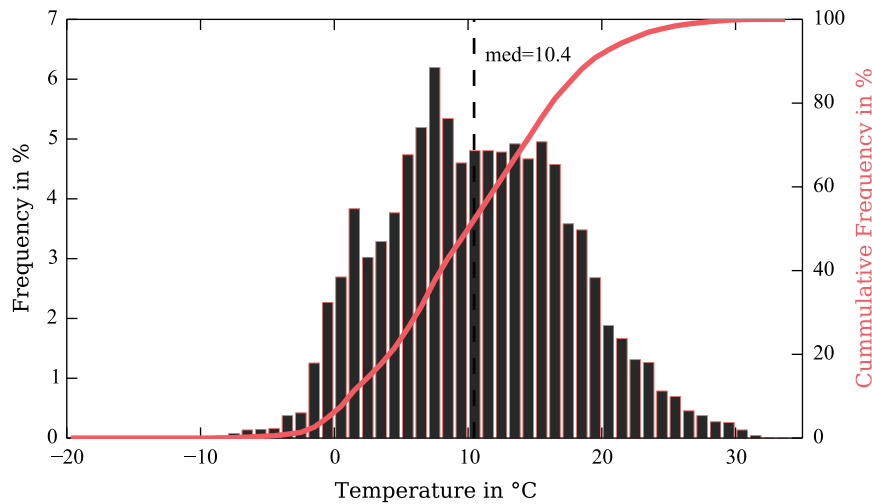


Figure 4.5: Histogram of test reference year air temperature for Bottrop

The use of TRY data for the prediction of PV power generation is not recommended. Fluctuations that occur due to clouds cannot be simulated appropriately as that frequency is usually higher than the hourly resolution of the reference data. However, for current simulations this data will be used to make rough estimations about the PV generation that is possible. In a later stage it will be possible to use more precise weather data from a different source.

Additionally to the TRY data, hourly recordings of the weather, i.e. air temperature, global solar radiation, wind speed, wind direction and relative humidity, from DWD weather stations in the project region of the year 2012 are available.

4.2.6 City District Information Model

As described in the last sections designing, simulating and potentially implementing DSM concepts in a smart city environment requires a huge amount of data. Therefore, even for the rather small 2DSM project district in Bottrop, it turned out that the collection of necessary data was a major challenge. Data about building size, window areas and material could only be concluded according to the building age and partially validated through an on-site analysis. However, even existing data about the regional infrastructure was distributed among public authorities or energy

Table 4.2: Required input data for city district simulations

Building level	City district level
construction dimensions	electric grid and trans-former specifications
construction materials	data on gas and district heating networks
distribution of facade surfaces	information on geological properties and groundwater level
energy conversion units	
energy delivery systems	
local (renewable) energy generation	local (renewable) energy generation

providers and therefore not easy to collect. Furthermore, all collected data, had to be formatted manually into a specific structure, which could be used for the simulations. Therefore, we decided to analyze in more detail the possibility of applying the Building Information Model (BIM) idea to the city district level. This City District Information Model (CDIM) is a conceptual idea of data management, which facilitates the energetic analysis, and simulation of whole city district areas. Within our project we have tested different approaches and quality levels for parameterizing our simulation, however it became evident that there is a minimum demand for data, which is necessary to perform a credible energy focused simulation on a city district level. While the previous sections presented the detailed input for the 2DSM project, table 4.2 shows in general the minimum requirements for building and city district data required to model a city district.

Such detailed data, however, is usually not easily available. Therefore, an investigation of suitable data sources was performed. Using BIM would allow to provide easily accurate and up-to-date building data. BIM is an integrated approach for building life cycle data management. Thus, once BIM is widely available it would be a very powerful tool to provide data for simulations of single buildings. However, when planning and simulating a whole city district it would become necessary to incorporate BIM data with further spatially referenced geographic data into a joint coordinate system.

In the past, basic spatial information like land register data were usually managed on the basis of local, paper-based copies. With the development of Geographic Information Systems (GIS), methods became available to electronically store, compile and access mapped data. Therefore, today public authorities manage some geospatial data in GIS databases. Typically, information about land use, ownership structure and construction years of buildings as well as basic information about local infrastructure are available. Also, GIS software is usually used by grid operators and energy suppliers and could potentially provide much more detailed information about the local infrastructure. Furthermore, precise energy consumption data with high resolution can be obtained dynamically from smart meters with bi-directional communication in the future. However, since there is only little distribution of smart meters in Germany today, dynamic energy consumption data is only available on city block level from the local transformer station, if available at all.

CDIM Concept

Necessary data collection and management bring along challenges and needs for new methods and tools. Whenever possible these should be adapted from both, GIS and BIM, and applied to a city district scale. In addition to BIM, interdependent and parallel simulation and analysis of buildings in a city district is required. Geographic information systems must be integrated with building models and necessary city district infrastructure data. Therefore, a concept is developed to merge all necessary data for modeling and simulation into a single information model for city districts, the CDIM. [37]

With the regularly available computational capacities, it is not possible to simulate and evaluate all potential energy systems of a city district within a single simulation. The CDIM should solve this problem by allowing to store and display preceding simulation results, thus facilitating an on-going improvement of the analysis process. In order to make simulation results even more accurate and to embed them in dynamic DSM, data automation becomes very important. Thus, it is crucial to have a database, that is frequently updated by all stakeholders.

Examples for technical appliances, which automatically synchronize data with servers and desktop clients while installed on site, can already be found in BIM and GIS applications [38]. Future data exchange is enabled by the communication interfaces provided by emerging smart meters. However, the inclusion of dynamic data is not restricted to energy flow measurements. Especially within the scope of a city district, current information on construction works and infrastructure management would be very useful. The availability of such information could allow combining already planned construction works with the establishment of micro district heating grids. Furthermore, based on WebGIS applications, CDIM should provide and manage data within a network structure and use standards, protocols and services of the web. This would allow each local user to interact by adding information on local excess CHP heat production or available PV electricity, which could be used for cooperative energy management. Such dynamic data handling requires object-relational database systems for spatial data. Such software solutions, however, already exist as of today. Exemplary, PostGIS would already meet several requirements of CDIM data management. Figure 4.6 presents an overview on the core CDIM components and possible existing foundations.

The Impact of the Available Data Base on Simulation Results

The main idea of the simulation is to examine the impact of different qualities of parametrization data on the thermal energy performance of residential buildings. Therefore a dynamic thermal simulation is performed three times for the same building with changing input data bases. The resulting energy requirements are then compared and discussed. For this analysis, an exemplary building with well-known parameters from our project area in Bottrop was chosen and a one-

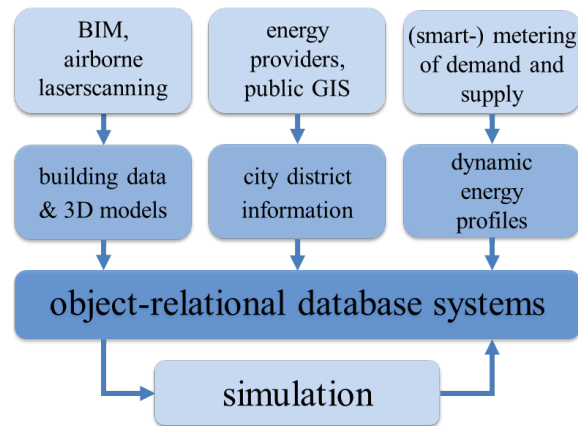


Figure 4.6: Core components of the CDIM concept

year dynamic thermal simulation was performed. The semi-detached building was constructed in 2004 and comprises a heated floor area of approximately 155 m² (figure 4.7, right side). The simulation was parameterized based on precise on-site observations of the building's dimensions and façade composition. The used thermal insulation standard was derived from the applicable German Energy Saving Ordinance (EnEV) [39] of the construction year and validated by a thermography analysis of the building's façades. The used supply system of the building is an air-water HP. The outcomes of this simulation are used as the base scenario representing a parameterization standard on BIM level, due to the extensive availability of the building data.

The first alternative scenario represents a typical simulation based on low data quality, as it is available through remote data collection (e.g. Google Maps). The building's dimensions are modified according to the accuracy of airborne laser scanning, which is approx. $\pm 10\%$ of typical house dimensions [40]. In this exemplary case, it was decided to assume that the measurement delivered 10 % larger values for the building dimensions. The façade composition (e.g. the size of windows) was assumed according to publicly available data about the correlation of construction year and building typology [41]. However, as often seen in our project, it is not easy to find exact details about the construction year of a given building. Often the data gathered from owners, residents and city administration showed distinct deviations. Therefore, in this scenario the construction age is estimated to be 2001. Since typically no information on the supply system is known, it is also assumed according to the estimated construction date to be a condensing gas boiler with an average efficiency of 104 % (referring to the lower heating value; [42]). The energy distribution is performed with a classical radiator based delivery system. The underlying gas prices are taken from the local energy provider, being 7.24 ¢/kWh + 11.9 €/month [43].

The third scenario represents a simulation based on CDIM data. Therefore, the thermal simulation itself is similar to the BIM data based scenario, however further information about the city district is available, which allows to create a sustainable supply system strategy for the observed building.

In this case, for example, information about the geological structures underneath the building, the availability of a district heating system and the available information on PV potential from Solar Atlas are analyzed [44]. Since the analyzed building itself is not suitable for PV generation due to its orientation, two cooperative PV scenarios with the neighbor building are examined. Solar Atlas indicated two neighboring buildings with large PV potential, each with a roof area of approximately 130 m² (figure 4.7, left side). In the first PV scenario, it is assumed that one of these buildings is already equipped with a PV system of 10 kWp with an expiring feed-in compensation. Due to the high penetration of privately owned PV systems in Germany such scenario will become very common in the future. Thus, the owner would be willing to sell his excess electricity at any price above the official European Energy Exchange (EEX) price [45]. In the second PV scenario, a new PV system is installed on the neighbor's roof, while the neighbor is allowed to use generated electricity for self-consumption at no cost in return. The remaining electricity then is used to power the heat pump taking into account the PV electricity production costs as of today [46]. As PV production costs are almost similar to the feed-in compensation, further feed-in revenues are not taken into account.

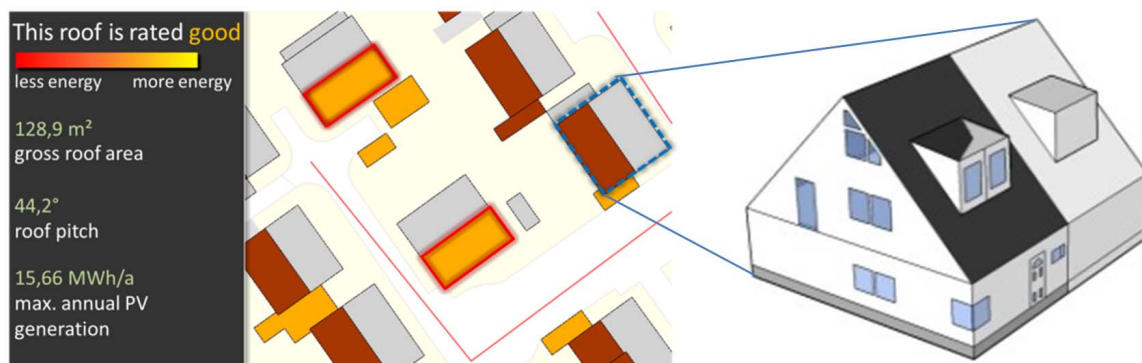


Figure 4.7: Left: Solar Atlas evaluation of building roofs - red squares, simulated building - blue dashed square. Right: The simulated building from our project area in Bottrop

For both PV scenarios the dynamics of PV generation are simulated according to PV generation profiles available from the EEX [45]. Furthermore, the electricity self consumption of the owner or roof space provider is subtracted from the generation according to standard load profiles available from energy providers [47]. The excess PV electricity is then used to supply the HPs electricity demand. Furthermore, a 500 l buffer tank is used to improve the match between PV generation and heat demand. Additional non PV electricity for HP operation is bought at the heat pump tariff from the local energy provider [43].

Table 4.3: Comparison of optimized energy demand and cost

	BIM Data	CDIM Data
Heating demand	10100 kWh _{th} 65 kWh/m ²	10100 kWh _{th} 65 kWh/m ²
Energy demand HP	3097 kWh _{el}	3097 kWh _{el}
PV energy consumption	./.	996 kWh _{el}
Electricity from the grid	3097 kWh _{el}	2101 kWh _{el}
Primary energy demand	8053 kWh	5462 kWh
Electricity provider cost	725 €	515 €
Electricity cost PV Scenario I	./.	> 40 €
Electricity cost PV Scenario II	./.	135 €
Total energy cost	725 €	555 – 650 €

Results: Heating Energy Demand

First, the energy demand for the building simulations based on assumptions and precise data is compared. Thereby, the total final energy demand for heating is approximately 12 % lower for the BIM scenario, as compared to the scenario without detailed buildings data. This difference, however, is based on deviations in size as well as construction standard. To isolate these effects the normalized heating demand per square meter is compared. The normalized demand is 4.5 % lower for the BIM scenario. This difference can be attributed to the deviations in the construction standard, while the residual discrepancy of 7.5 % is induced by the differences in building dimensions. Based on the current energy tariffs of the local energy provider, resulting energy cost are 23 % lower when BIM data is used. Furthermore, the resulting primary energy demand for the BIM scenario is 36 % lower than in the assumptions case.

Results: Energy Management on City District Level

Based on CDIM data the best opportunity to optimize the heating system is based on integration of PV electricity generation into the heat supply. Simulations show that thereby energy costs can be reduced by another 23 % as compared to the BIM data scenario. The primary energy demand can be reduced by 32 % through the CDIM based optimization. Table 4.3 shows the details of the optimized energy scenario in comparison to the BIM scenario.

The main idea of energy based city district simulation is the development of optimized often-named “smart” energy management solutions. The simulated scenario of local on-site integration of generated PV electricity was used to demonstrate the potential of such an optimization. While the building’s heating demand is not changing based on additional city district information, the simulation has shown, that electricity cost can be reduced by up to 23 % and primary energy consumption could be even lowered by 32 %. The extent of cost and energy reductions depends

strongly upon chosen building, construction standard and supply system. However, the reduction in primary energy consumption of 57 % between the data assumption scenario and the CDIM scenario indicates the huge impact of input data quality in city district simulation. To visualize this impact, figure 4.8 presents the resulting daily primary energy demand over the simulated year for each scenario.

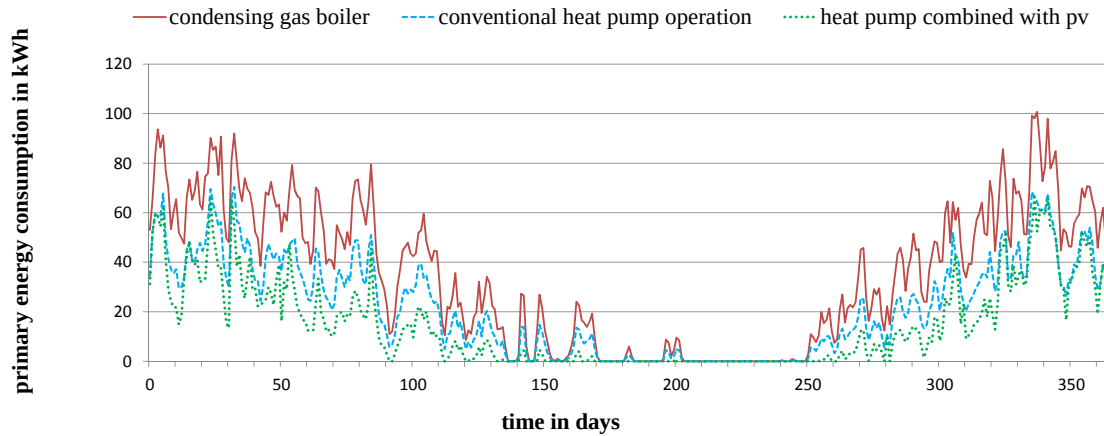


Figure 4.8: Resulting primary energy demand

In our analysis, a distinct correlation between data demand and the accuracy and validity of simulation results is shown. However, digital storage of CDIM data and a possible personal reference involve issues of data privacy. This applies in particular when consumption data with high resolution is combined with an address register. Thus, conclusions on personal behavior, presence profiles or living conditions could be deduced. Currently, there is an unclear legal situation in many countries and standard guidelines are under development. While, the data availability is crucial, factors of necessary data privacy need to be focused and carefully considered. Therefore, data should be anonymized by aggregation, whenever possible without loss of value. Furthermore, data base management systems, that assign different data access rights to different user groups, are required for the implementation of CDIM. Modern web applications could be used to securely store encrypted data distributed among different servers without direct personalization. Additionally, case specific data-access approval mechanisms similar to these known from online banking could be embedded.

Finally, CDIM could offer a communication platform, where neighbors within a city district are enabled to communicate and develop cooperative energy supply scenarios. For example, someone willing to install a larger CHP unit might cooperate with someone close by, who indicated the need for a new heating system. Additionally, based on the available information, companies could contact directly one or more house owners, request access to further data and, if desired, compute possible energy management or contracting solutions. While the concept is designed based on the

requirements of city district simulation, further applications are possible. Thus, CDIM could become a valuable tool for urban planning as well as for the development of traffic and transportation concepts.

4.3 Models of City District Energy System Components

A variety of energy conversion systems can be found in city districts. In residential areas that is mainly systems for space heating which are gas or oil fired. Most other household appliances use electricity. So the energy transport networks within cities are normally electrical and natural gas networks. Some areas especially in eastern Germany also use district heating with according hot water networks.

In the following sections, the variety of models developed and implemented during this project and used for the further investigations will be presented.

The component models described in this section focus on the flexibility for the electrical grid. However, energy conversion models that connect to the gas network or district heating exist already. Individual BES models are implemented in the object oriented modeling language Modelica [48] for physical systems. Using Modelica it is easy to make adaptations and extensions to the models to suit future needs.

4.3.1 General Model of BESs

Building energy systems can be used to make flexibility available for the electrical grid. The thermal behavior of the buildings will therefore determine the operational constraints of the heating systems within the BESs. Within certain bounds it is possible to operate the energy supply systems without affecting the thermal comfort of the occupants.

In order to obtain realistic behavior of a simulation the system components must also show a realistic behavior. Usually the behavior is more realistic the more detailed the models become. However, there is a trade off between model detail and parameterization effort of models, simulation speed and stability. Therefore, it is necessary to find a compromise between the detail of a model and negative side effects that go along with it. Unfortunately, it is not exactly known what level of detail is necessary for the examination of complex BES as the interaction and important emerging effects are not yet fully understood.

The described models are not fully physical models but to a great extend are black box models with non-linear behavior. This immensely reduces computational effort but still leads to good accuracy of results. The models are detailed to a level that hydraulic circles with specific media properties are computed. The models can predict steady state behavior well but have not been validated for

good dynamic behavior in all cases. Using Modelica as a modeling language and its object oriented modular approach it is relatively easy to substitute or extend models if necessary.

Domestic hot water usage is not modeled at the current stage. In order to implement this it is necessary to generate a water usage profile which should be synchronized with the occupancy profile. Currently there is no profile generator available that includes profiles for lights, machines, occupancy and hot water.

As a principle to follow for the system control it will be assumed that the thermal comfort must not be affected by the DSM. So the occupant sets limits to the management process in two ways. Firstly the thermal comfort boundaries will not allow turning on or off the heating devices for too long. Secondly the occupant's behavior like ventilation or using machines will affect the zone temperature which in turn will affect the heating system behavior. Since most household appliances use electrical power the user will also directly affect the electrical grid in a hard to predict way.

All BES are modeled in a way that they can be automatically parameterized and exported for the simulation platform based on the chosen scenario. This is important considering the large amount of buildings with individual supply systems in a city district.

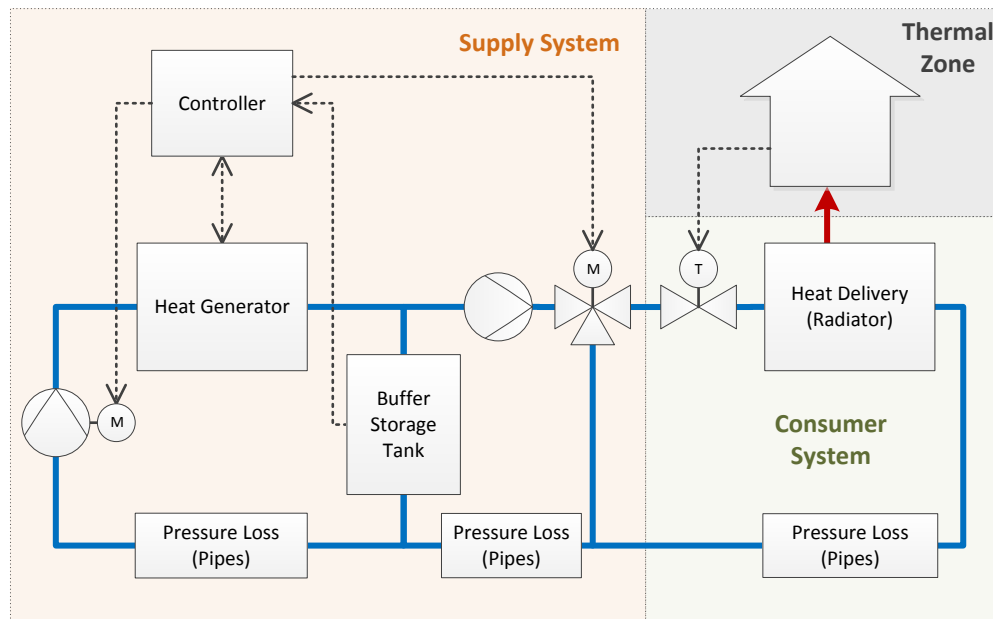


Figure 4.9: Heating supply system structure.

The system models described in the following sections are similar in their structure (fig. 4.9). A simple circuit model with a heat generator, a buffer storage tank for hot water and a consumer circuit with a circulation pump and the heat delivery system was chosen. In order to easily select between different heat generator or heat delivery models the generator and consumer part are split into separate objects. During the process of model compilation the correct model types will

be selected according to the parameterization. In Modelica parameter sets can be defined with *records*. In the described libraries most of the model parameters are organized within records assigned to components like building zone, supply system, heat pump, radiator, pump, valve etc. This way many thousand different parameter values can be stored hierarchically in records. For automatic scenario setup the records itself can be generated automatically and be stored as text files accessible to the Dymola C-code generator.

The supply record contains information about the system type of the generator and supply part of the heating system. Additionally, all necessary information for the supply system components must be selected in the database (records). The selection of appropriate hardware will be done in an automatic process that is implemented in a script framework in Python. Based on the thermal zone's design heat power and according to the simulation scenario which house contains a heat pump, a CHP etc., the appropriate hardware is selected. During the translation process into C-code (equal to the thermal parameters, see above), this information will be compiled into the model.

Direct compilation has the advantage that the model can be evaluated for constant variables before simulation to optimize simulation code and improve the simulation speed. Also the parameter assignment with the exported C-code inside the simulation platform can be avoided. A drawback might be that simulation parameters cannot be changed after translation (for parameter variations on the simulation platform for example). However, most parameters in the models are connected with each other and therefore cannot be changed independently. Furthermore, interesting parameter changes like the size of the buffer storage would require changing a record which is currently not possible in Modelica.³ Structural changes in the models like buffer discretization or selection of a different heat generator would of course require re-translation in any case.

Each supply system has an internal control that follows three principles:

1. buffer storage charge control will ensure sufficiently high temperatures in the tank
2. security checks will assure temperature limits of the heat generator system
3. flow temperature control for the consumer circuit will avoid temperature fluctuations in the delivery system

The first two rules will override external control signals. Only in a given range of the operational envelope of the heating system external control signals will be allowed to take precedences over the internal control. Figure 4.10 shows how the final control signal is determined.

From the buffer state (empty, half filled, full, etc.) the internal control will decide if external control signals may be processed or not. As a result the system can be in a state of “on” when the buffer needs to be charged, “off” when the buffer is full and needs to be discharged and “id” when the external signal may be used to operate the heating system. This buffer state concept is illustrated

³A workaround can be to change each record scalar value on its own. This however would require to change many parameters which complicates the process and which should be avoided in the first place.

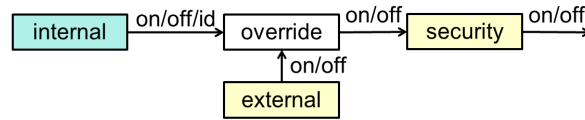


Figure 4.10: Selection of heat generator control signal.

in figure 4.11. The region *high* and region *low* create buffer regions of 10 % in relation to the limits. Of course, this range is adjustable.

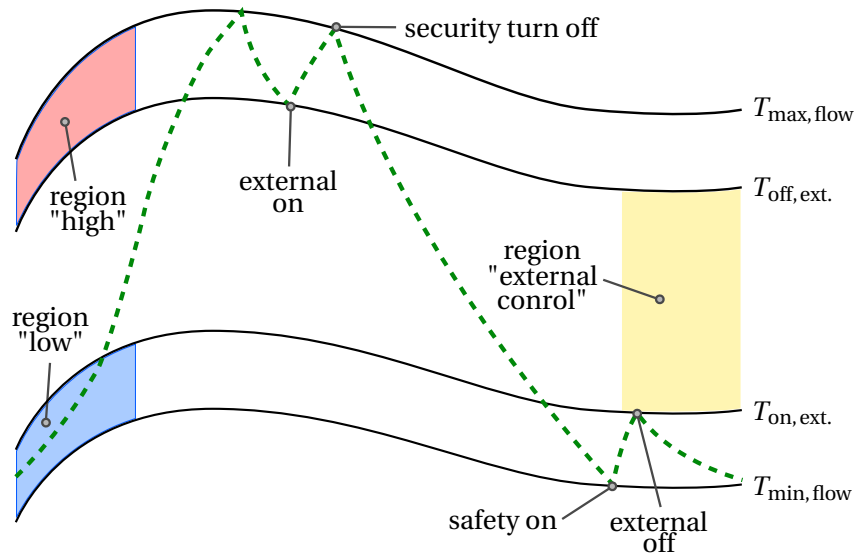


Figure 4.11: Illustration of external signal selection as a function of buffer charging state.

Even though the basic functionality of the controllers is the same in all supply models, the controller is specific for the heat generator. For example interfaces are unique for each device type. Therefore, each heat generator implementation needs a specifically adapted control algorithm and controllers may not simply be exchanged with each other.

The circulation pumps for the heat generators and the consumer side both use a characteristic pump curve that defines the relation between volume flow and pump head. The heat generator pump is taken from the public *Modelica.Fluid* package. The zero-delivery head as well as the maximum volume flow are computed from the maximum power of the heat generator to always ensure sufficient volume flow.

The consumer pump is taken from the institute's model library as this model provides volume-flow control. This means that the pump will control its pump speed to attain a given value of volume-flow and pressure increase. Between the points of design volume-flow and zero-flow the pump head will descent linearly to half of its design value. This is a standard control scheme to reduce energy consumption when strong flow restrictions occur in the consumer circuit (closed thermostatic valves). The characteristic curve at design speed must be selected from a set of records,

basically defining the pump size. In order to define the design point the maximum energy demand of the building and the design temperature difference of the radiator type is used to ensure sufficient volume flow. Another measure for energy conservation is the selection of a minimum pump speed during night time. This behavior is activated by default.

In the buffer storage tank energy will be stored. This decouples heat generation from consumption and therefore adds flexibility for heat generator operation. Stratified storage tanks are commonly used in heating systems. In these systems a stratification of hot and cold water layers is employed to provide high temperatures for the consumer as long as possible. Hot water will be added at the top and cold returning water will be injected at the bottom of the tank. In order to model the stratification the water volume is discretized vertically into layers. Each layer is representing a volume of one temperature. Adjacent layers will transport energy by convection and conduction. The quality of the stratification effect observable will depend on the number of layers. Obviously, a high discretization will reduce simulation speed why we choose a low number of ten layers in our simulations. Usually the high volume flow of the heat generator pump will reduce the stack effect in the buffer anyway.

The buffer has two positions to measure temperature, one at the top and one at the bottom of the tank. These two signals will be used in the buffer charge control to decide when the heat generator needs be turned on or off. In general, when the top sensor experiences a temperature at the lower boundary of the defined temperature range the generator will start up. If the bottom sensor then measures a temperature at the upper limit of the defined temperature range the generator must be turned off again (also see fig. 4.11). The lower limit can be chosen as the current heating curve temperature because the flow temperature should not fall below that value. The heating curve is a function of design room temperature, outside temperature, flow and return temperature and radiator type. For an average outdoor temperature the curve will give the necessary flow temperature. Figure 4.12 displays curves for three different heating systems with 110 °C, 90 °C and 55 °C flow temperature and always 20 °C room temperature, respectively.

For the DSM control a buffer energy state signal is needed that tells the algorithm how much energy is stored in the buffer. With this information the algorithm can decide when the buffer approaches an “empty” state or when the buffer will be “full”. This signal will be calculated in the supply model and passed on to a higher level energy management system. In order to assess the state of the buffer storage the energy content of each layer will be determined with respect to minimum energy level that is set by the current ambient temperature (room temperature). In reality the temperature distribution in the buffer will be measured for this purpose, maybe only top and bottom temperature can be used to come up with a guess.

Pressure losses in hydraulic circuits are handled equally for all supply system types. A lumped pressure loss is modeled in each circuit. For the heat generator circuit pipe length and single resistances will be transformed into a respective flow resistance factor (ζ -value). In case of the con-

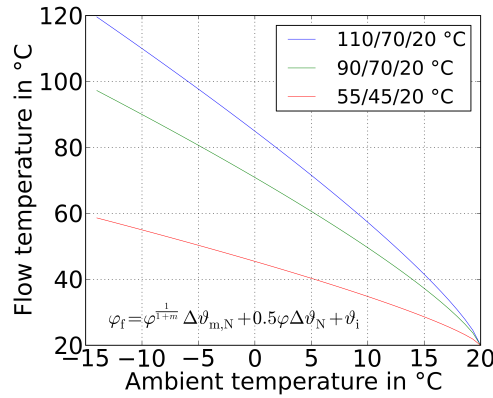


Figure 4.12: Heating curve for three different heating systems.

sumer circuit an average pressure loss based on house type and size will be estimated using a set of equations given in DIN V EN 18599 [49, Sec. 6.3.1.2 ff.]. The calculated pressure loss for design conditions will be transformed into an equivalent head loss factor and used for dynamic pressure loss calculation. Currently, heat losses in the distribution network will not be considered in the simulations.

Building Envelope

The model for the thermal behavior of the building structure is based on German industry guideline VDI 6007 [50] also known as 2-C (two capacitor) model. Figure 4.13 shows the graphical model representation. A building is modeled as a single heating zone with two main components, heat transfer and storage analog to electrical resistances and capacitors in an electrical circuit. In comparison to a detailed model with multiple walls with discretization, this approach decreases the model's number of parameters and consequently the number of equations as well as the computation time. The drawback of this simplified approach is a slightly lower accuracy compared with high detailed models. A detailed description of the model and validation can be found in [51].

The parameterization of the simulation model requires to convert geometric and material properties of the house into equivalent resistance and capacitance values for the inner and outer thermal masses (walls, ceiling, floor, ground slab etc.) This process is described in VDI 6007 [50]. For the simulation platform an automatic process has been developed that converts all the geometric and material properties into an XML representation that can be processed by a separate conversion tool. Among other parameters unique for the zone these values are stored in a database inside Modelica (Modelica records). Each thermal zone can then be assigned with the appropriate data set. The assignment of the data sets to the specific thermal zones is done in an automated way before the models are exported as C-code which can be integrated in the simulation platform as described in section 4.4.3 (Entity Layer (EL)).

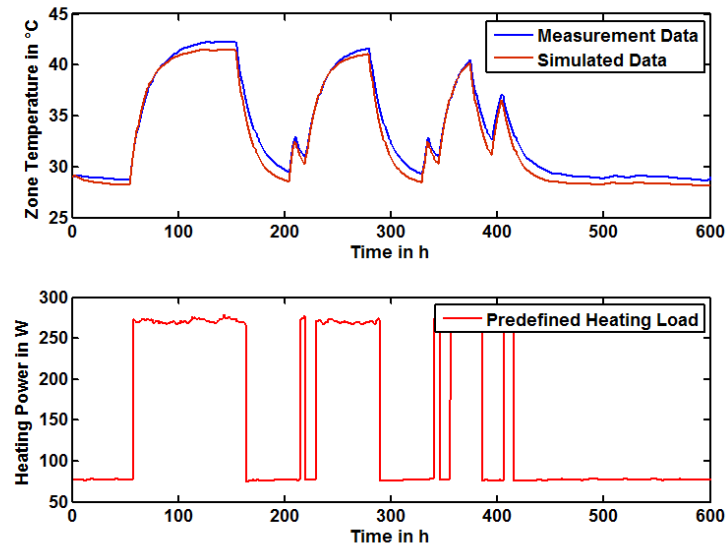


Figure 4.14: Comparison of measurement and simulation data of the thermal zone model

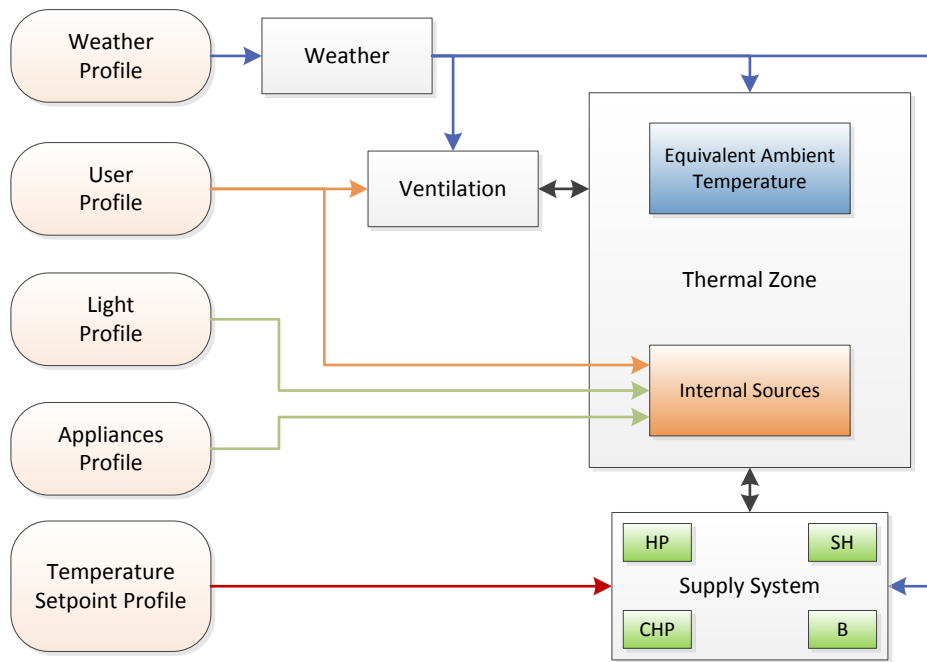


Figure 4.15: Interconnection of BES components and thermal zone

perature the heat production is assumed to be 95 W. According to the set point temperature of the room heating system an additional amount of heat will be supplied by the heat delivery system (radiators).

The amount of air exchange can be a constant value as it is often used for energy calculations in

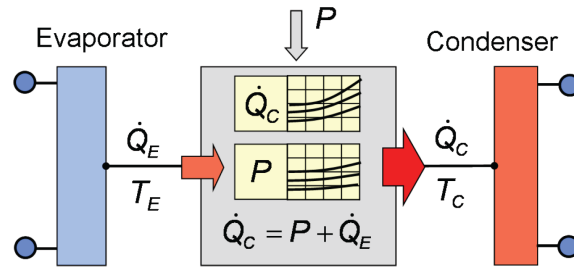


Figure 4.16: Scheme of the table based HP model [54].

industry standards (e. g. [53]). This also would be a good assumption for mechanically ventilated buildings. Residential buildings in Germany often only use natural ventilation which is considered in all BES described later. The simulation models will use a dynamic ventilation rate that is dependent on the people's activity (more ventilation when people are active/present), outside temperature (less ventilation at low outside temperatures since people will open windows more often in summer), room air temperature (the higher the temperature indoors, the higher the probability that people will open windows). Additionally, there is a constant ventilation rate assuming leaks in the building envelope.

BES with Heat Pump

The HP model is a black box model consisting of two heat exchangers connected by the HP circuit (see fig. 4.16). Given a specific electrical power, the temperature of the evaporator and condenser a heat flow between the two heat exchangers will follow. Tabulated values for electrical and thermal powers will be taken from the manufacturer. A description of the HP is given in [54].

The HP can be power controlled. However, most small scale HPs on the market will be switchable between on and off and not be power controlled. This is reflected in the controller signal for the HP and its circulation pump.

Buffer charging has been described briefly on page 35 f. The minimum flow temperature is set to the current heating curve temperature. In case of a HP system it is reasonable to limit the maximum flow temperature to a low value. This improves the efficiency of the device but limits the time of operation and increases on/off switching. Here a value of 10 K above the heating curve has been chosen. This way the maximum device temperature will not be reached even at maximum heating curve values (very low outside temperatures).

The maximum device temperature is taken from manufacturer data and is usually around 60 °C. In the security module this condition will be asserted. In case of overheating the HP would be turned off. A restart lock mechanism would prevent the HP to be started before a designated time of 900 s has passed.

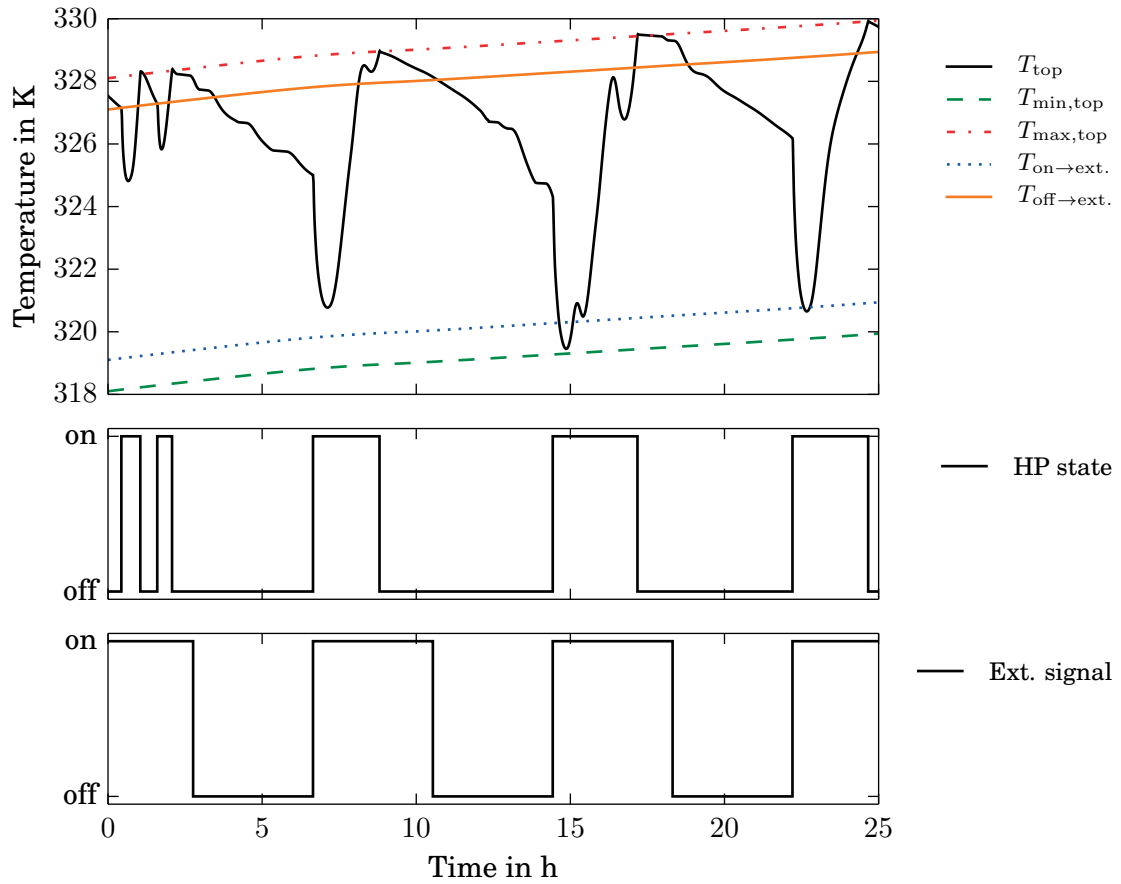


Figure 4.17: Exemplary result for HP operation with alternating external signal

Figure 4.17 shows an exemplary simulation result of the HP operation. According to the external control signal (bottom graph) one can observe how the buffer state (temperature, top graph) moves between the minimum and maximum temperature ($T_{min,top}$, $T_{max,top}$). When the buffer top temperature reaches the maximum the HP will be turned off regardless of the external control signal (compare time < 2.5 h). As soon as the temperature falls below the *high region* limit $T_{off \rightarrow ext.}$ and the external signal is at on then the HP will turn on. When the temperature is turned on, a temperature drop of the buffer temperature is observable. This is due to the sudden increase of the condenser volume flow when the heating power of the HP did not reach its final level. For a period of time the buffer's top temperature will reduce until the buffer's bottom temperature (flow temperature for heat generator) reaches higher values.

The second graph shows the actual operation status of the HP. It will only operate when the external signal allows. In this case the house has a low energy demand and the buffer will be emptied slowly. Therefore, the minimum temperature $T_{min,top}$ is never reached. In this case the HP would turn on even if the external signal was off.

In contrast figure 4.18 on page 43 shows the HP behavior without an external control signal. Here

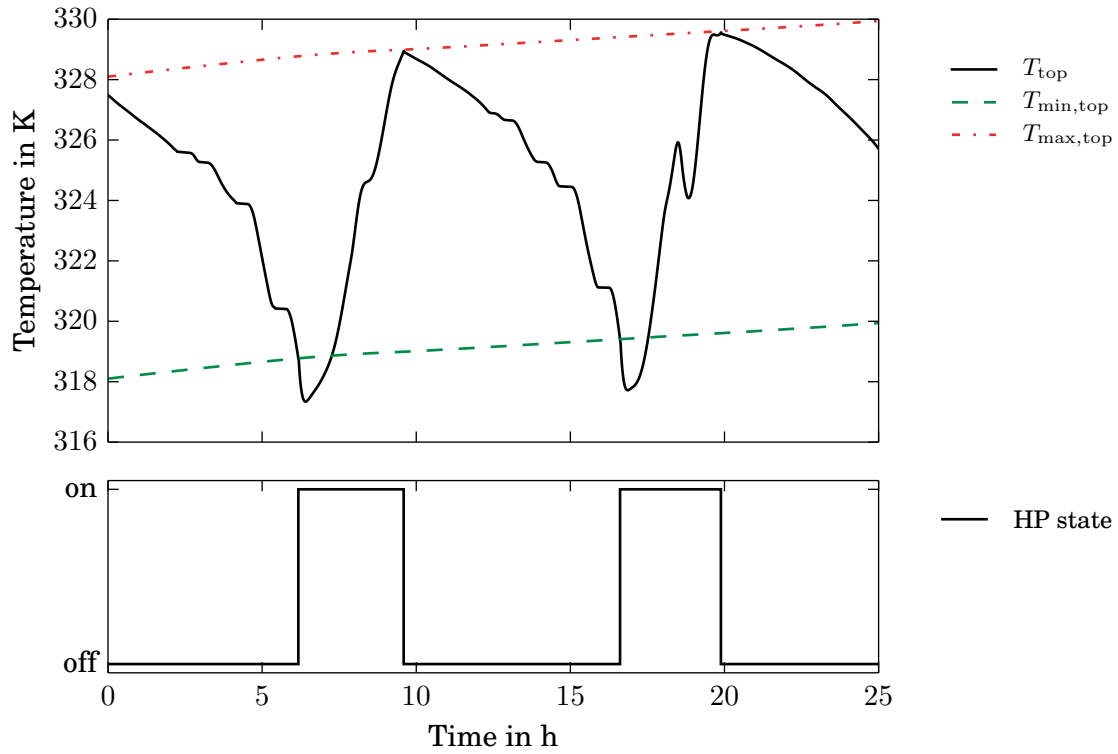


Figure 4.18: Exemplary result for HP operation without an external control signal

HP will only turn on when T_{top} becomes smaller than $T_{\text{min,top}}$ and will turn off when $T_{\text{top}} > T_{\text{max,top}}$. Consequently, this control will lead to the lowest number of system starts.

BES with CHP

Like the HP model the combined heat and power (CHP) device is a table based black box model. The basic behavior of the control is comparable to the HP controller. There is a minimum and maximum temperature ($T_{\text{min,top}}$, $T_{\text{max,top}}$) which will control security turn on and turn off of the CHP. Figure 4.19 on page 44 shows the CHP operation with an external control signal. When the CHP was turned on because of low temperatures (e. g. $t > 20\text{h}$) external control will be regained only when the temperature rises above $T_{\text{on} \rightarrow \text{ext.}}$.

An internal controller will set the power level of the CHP (“CHP state”) to reach a target flow temperature (T_{set}). This control temperature will be switched between a lower and an upper value. When there is an external control signal requesting CHP operation the upper set point value will be chosen as the maximum return flow temperature plus the design temperature spread (usually 70°C and 10K). When there is no external signal the lower value will be chosen. This is the mean temperature of maximum device temperature and the current heating curve temperature. This way the system energy losses will be reduced and the efficiency of the CHP is increased (at part

load conditions) when external control is turned off and the system controls itself (i. e. reference case, not displayed here).

According to the power level of the CHP (usually controllable between 30 % and 100 %) a thermal and electrical power output will be calculated. Dynamic effects like slow thermal power output change at startup or shutdown is not considered realistically in the model but a simple ramp function will handle electrical and thermal power output. The internal controller has a set of security checks. It is possible to select between thermal and electrical power control. In the implemented model thermal power control was used.

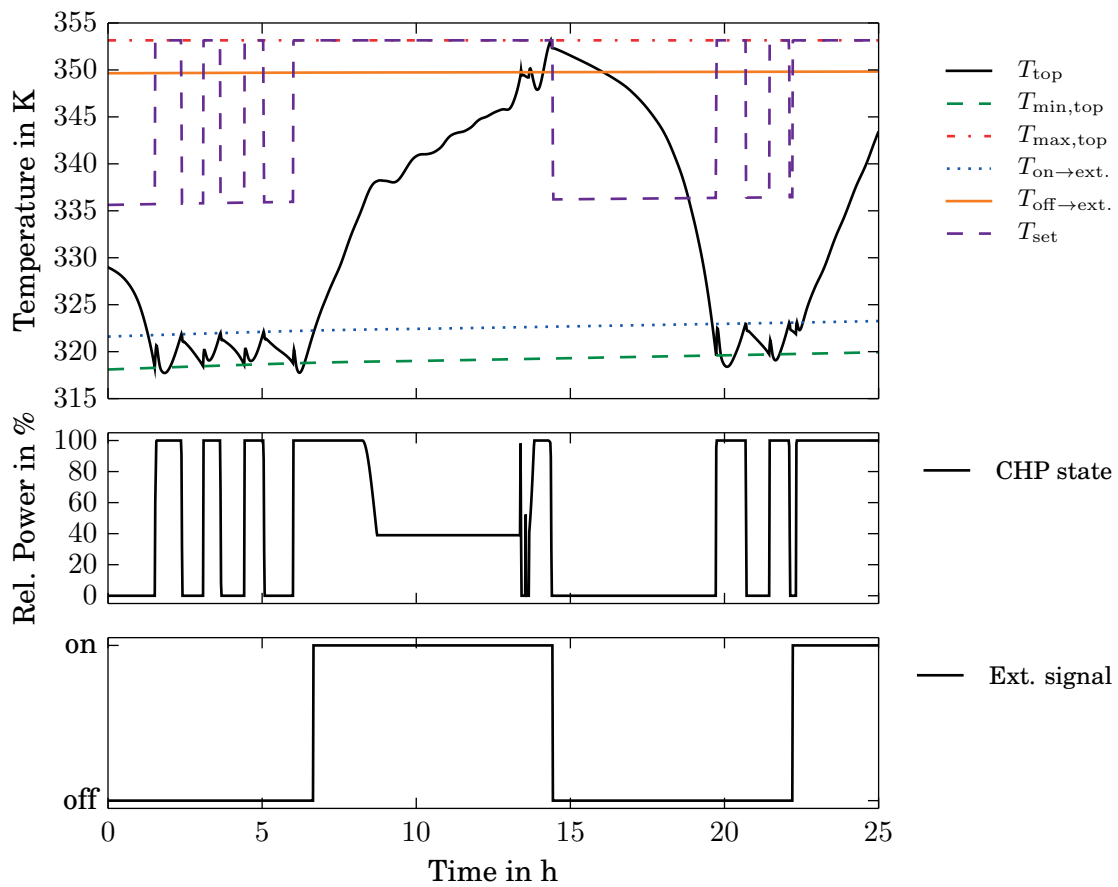


Figure 4.19: Exemplary result for CHP operation with alternating external control signal

BES with Storage Heaters

Night Storage heater has been a widespread heating device in the past years. This system typically consist of an electrical heater integrated in clay bricks that serve as thermal storage. As the name indicates, this device is designed to operate during over night using cheaper off-peak electricity to store heat and deliver it during the rest of the day. The heat delivery is carried out through radiation

and free convection or in combination with a forced convection through a fan.

The implemented model is based on the WSP 2010 [AEG Haustechnik]. The model comprises a charging module and a room temperature control unit. The room temperature is regulated by a fan which is operated in a non modulated mode using a hysteresis of $\pm 2^\circ\text{C}$ to maintain the zone temperature within the thermal comfort standards.

The night tariff is set empirically to the time slot between 21:00 and 7:00. It is assumed that all heaters in the city district will belong to the same group that will be turned on and off by the energy supplier at the same time. In the charging module, the outdoor temperature is used as an input to calculate the state of charge (SoC) for the next day's corresponding heat demand. At -14°C the storage heater's charging duration is set to 12 hours at which the full storage capacity is reached, while at 20°C the charging duration is set to zero. The charging module takes into consideration the remaining heat from the previous charging period and reduces the new charging duration accordingly. An overheating safety module is implemented to interrupt the charging if the temperature exceeds 600°C .

An additional charging strategy is integrated into the night storage heater to enable a renewable energy oriented operation mode independent of the night tariff and strictly oriented to the availability of the RE generation. In this mode an external signal can turn the heater on and off according to the amount of renewable energy available. Like for all other supply systems the heater's internal charging control will override the external signal in case of too low or too high temperatures.

BES without Electro-Thermal Heating System

In order to perform accurate analyses of city district energy systems, also the BESs without an electro-thermal heating system have to be represented as they still have an electrical power consumption which has an impact on the operation of the electrical grid. To be consistent with the setup of the simulation platform non-electro-thermal heating systems will also be modeled in Modelica. The models can then be exported like any other heating system type.

The simulation models will read the respective profiles for electrical power consumption of machines, appliances and lights. In the case of photo-voltaic power generation the current power will be computed and feed to the simulation interface as current electrical load. Like in the other supply models it is assumed that the generation can be fully used to compensate the internal power demand of the appliances and lights.

A simulation of the thermal behavior of the building in combination with an ideal heat source will provide an estimation of the heating end energy demand of the respective building. This information can be used to compare the thermal demand forecast of a control algorithm with that of the actual simulation model. As hydraulic components will not be simulated in this model, the simulation speed is higher. In most scenarios the majority of buildings are of this type and therefore the

reduction of computational effort is advantageous for the whole simulation.

Heat Delivery Models

The heat delivery model currently used in the simulation environment is a radiator model with a thermostatic valve to control heating power. A set-point temperature profile can be given by a table individually for each building.

The radiator is discretized in vertical layers and delivers heat by convection and radiation. The radiator type and all important characteristics can be selected from a record. Design flow, return and room temperatures define the radiator's characteristic. Deviating conditions will result in different thermal power as for real radiators. A list of heaters from manufacturers is available in the model library of the E.ON ERC. The radiator provides good static and dynamic simulation behavior.

4.3.2 Models of Energy Supply Networks

Electrical Grid

The grid data from the model area in Bottrop, Germany, was provided by the energy provider ELE Verteilnetz GmbH. The provided data included:

- ▷ Grid topology at low and medium voltage level
- ▷ List of the public and private substations
 - Address
 - Transformer manufacturer
 - Type
 - Short-circuit voltage
 - Nominal capacity
- ▷ Operation conventions and standard equipment
 - Cables at low and medium voltage level and branches
 - Nominal capacity of the substation transformers
 - Voltage at low and medium voltage level
 - Grid operation structure at low and medium-voltage level (meshed or radial)
- ▷ Installed cables at low and medium voltage level
 - Connection points

- Installation date
- Length
- Type
- ▷ Installed generation units
 - Address
 - Type
 - Nominal power
 - Voltage level
- ▷ Load profiles for temperature-dependent and interruptible consumption units
 - Night-storage heater
 - Heat pumps
- ▷ Standard load profile for residential buildings

The electrical grid was modeled in the software tool Neplan, which can be used to analyze, plan, optimize and simulate electrical, water, gas and district heating networks. The model is presented in 4.20.

The provided highly detailed data of the medium voltage level were directly integrated into the model. At low voltage level, various assumptions had to be made due to the lack of information. In order to collect more information, the model area was scanned using Google Earth to map the grid topology to the real infrastructure. To determine the length of the cables between nodes, buildings were considered as starting and ending points and the distance between the points was measured. The supply power cable for the street is assumed to be installed in the middle of the street. The length of branches is determined similarly to the length of cables between the nodes.

The taken assumptions are not considered critical, as for the purpose of the simulation, the testing of energy management algorithms and investigation of the effects on the voltage profile of the grid, deviations in the range of a few meters are not significant.

4.4 Co-Simulation Platform

4.4.1 Requirements for City District Energy System Simulation Platforms

The simulation of a system as described in section including several hundreds of heterogeneous BESs is computationally challenging due to three requirements. First, the models have to be represented detailed as introduced in section 4.1 in order to provide the necessary information. Second, the analysis of energy management algorithms for city district energy systems involves a large

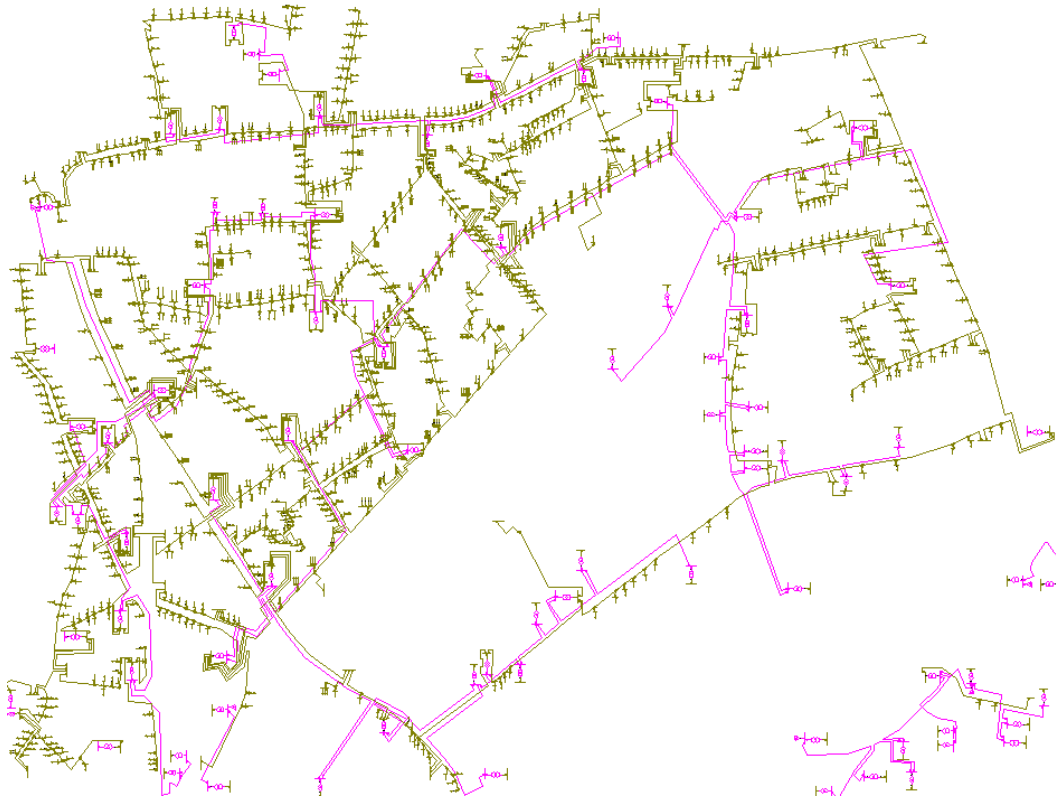


Figure 4.20: Model of the electrical grid in the project area in Bottrop, Germany

number of individual BES. And third, it is required to simulate those large systems for long time periods, e.g. several weeks or up to a year, in a rather short computational time. The simulation of long time periods is necessary to generate meaningful results which depend not only on a selection of individual days. A short computational time is appreciated as it allows to run simulations with different configurations and execute comparisons. Furthermore, the simulation of the described system comprising several different domains. In order to simulate such a system, all the different models could be implemented in one modeling and simulation environment. However, in general for the different domains involved, specific modeling and simulation tools already exist, providing reliable and widely accepted libraries. Thus, the here presented approach to simulate a multi-domain system is to combine different simulation tools in a co-simulation. A more technical description of the here presented simulation platform is given in the publication [55].

4.4.2 Related Work and Literature Review

In the literature several simulation tools for analyzing residential energy systems as introduced in section 4.1 have been presented. The development of those simulation tools was also mainly driven by the requirement to simulate a residential energy system in order to investigate control and energy management algorithms. The simulation platform developed within the project 2DSM

differentiates by the available platforms through the focus on high performance, scalability as well as practicability for professional applications. Nevertheless, the 2DSM simulation platform leverages on the experience and the findings of the work summarized in the following paragraphs.

The simulation tool presented in [56, 57] and [58], called IDEAS tool, is based on a Modelica library comprising models which allow to compose a complete model of a residential city district energy system. The simulation of the composed model is then executed in the modeling and simulation environment Dymola [59]. The approach to implement the whole model in a single Modelica model raises two main problems: First, all known Modelica solvers are single-core applications, thus the simulation of large scenarios cannot leverage on the computational capability of modern multi-core machines. Second, Modelica as a modeling language for multi-domain physical systems does not allow to implement sophisticated energy management algorithms in a convenient way. Thus, the analysis of energy management algorithms would require the coupling of the Dymola simulation with a different simulator which allows the implementation of energy management algorithms.

In contrast to the IDEAS tool as described in the previous paragraph, other approaches show how different simulators can be combined to one simulation platform. This approach allows using specialized tools for each involved domain. The advantage of this approach is that existing libraries in a certain tool can be reused without reimplementing in a different modeling language and environment, thus, increasing reliability and usability. The approach of coupling different simulators is very common in the field of co-simulation of power systems and communication systems and has been presented in several works [60, 61]. The coupling of different simulation tools to perform a co-simulation requires a so called runtime infrastructure (RTI) which provides the time synchronization and data distribution among the incorporated simulation tools.

The approach of coupling different simulators to a co-simulation platform has also been applied in the field of residential energy systems. The most known works are Building Controls Virtual Test Bed (BCVTB) [62] and MOSAIK [63, 64]. In [62] the authors demonstrate the coupling of EnergyPlus [65] to simulate the buildings and the modeling and simulation environment Dymola [59] for simulating the HSs. The authors mention that the long lasting computation times can be decreased by starting several instances of EnergyPlus. However, this requires a manual setup of the parallel simulation. Furthermore, the coupling of EnergyPlus and Dymola does not incorporate a tool which allows to implement higher level energy management algorithms. MOSAIK represents a very interesting approach for an RTI. MOSAIK aims at providing automatic composition of simulation scenarios based on individual models which can be implemented in different simulators. This allows to reuse existing models and simulators. In order to enable simulators to be compatible with MOSAIK, the simulator has to be wrapped in several interface layers. The focus of the work is on the semantic description of the models and the simulators which allows the automatic composition but not on the simulation performance.

The approach of GridSpice [66] is to exploit parallel computation capabilities by executing different parts of an electrical network or different parameters sets in parallel. The focus of GridSpice is the simulation of transmission and distribution grids in combination with market models. In contrast to the here presented simulation platform, GridSpice has not been used to simulate residential energy systems including thermal models of individual buildings.

4.4.3 Approach of City District Energy System Simulation Platform

Introduction

The approach of the here presented simulation platform is to combine commercial-off-the-shelf simulators with existing and reliable libraries to a co-simulation platform which allows for analyzing energy management algorithms for large residential energy systems. Referring to Figure 4.1, three functional subsystems have been defined and are simulated within the simulation platform in individual but coupled layers: entity layer (EL), network layer (NL) and system control layer (SCL) as shown in Figure 4.21. The partitioning of the system is motivated by the fact that for each subsystem powerful simulators and libraries exist. Within the entity layer the BESs including application control level are simulated, within the network layer the various energy supply networks and within the system control layer the energy management algorithms. The time and data synchronization required for performing a co-simulation is provided by an RTI.

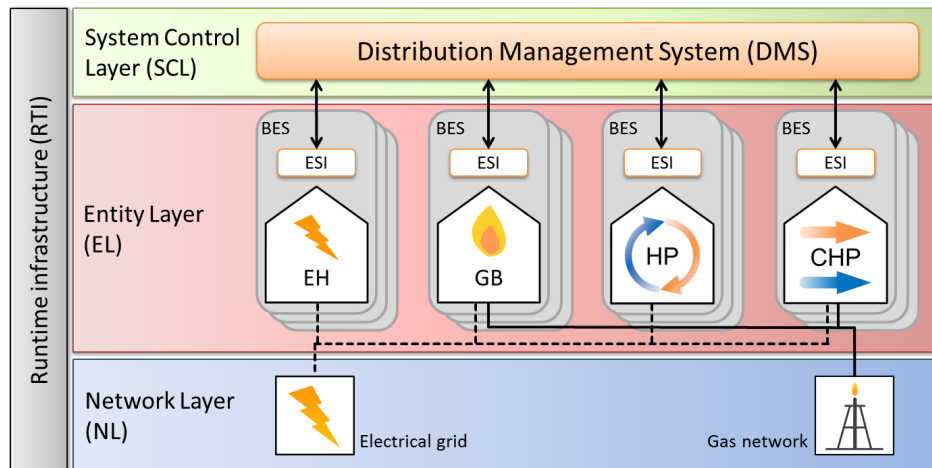


Figure 4.21: Schematic of a sample city district energy system and the partitioning into the layers of the simulation platform

The development of the simulation platform aims at exploiting parallel computing capabilities of modern simulation servers or workstations. Parallel computation has been applied here on two different levels. First, the execution of the simulation within the individual layers has been parallelized as much as possible. Special focus has been on the parallel execution of the individual BES

models within the EL. Furthermore, the individual layers can be executed in parallel or in series depending on the simulation mode in each individual layer. For example in case of time continuous simulations within two layers, the execution of the simulations would be executed in parallel and the simulations would exchange the values of the coupling variables at defined time steps. This time step is commonly referred to as macro time step (MTS). Internally, the simulators can use smaller time steps called micro time step (μ TS). If the coupling variables are highly dynamic, MTS would be chosen rather close to the μ TS in order to track the interactions between the partitioned simulations. In the case of slower dynamics, the MTS could be chosen much larger than the μ TS. In the case of the coupling of a time continuous simulation in one layer with a discrete time simulation in another layer, the execution of the simulations should be executed in series. For example, the simulation of the BESs would be executed for a certain MTS. The resulting values representing the electrical power consumption of the BESs could be then inserted in a load flow calculation of the electrical network which is executed while the BES simulation is paused. The results of the load flow calculation which is a snapshot analysis could then be used as input for the BES simulation in the next MTS.

Entity Layer (EL)

Regarding the parallel execution of the simulations within the individual layers, the main focus regarding parallelization of simulations has been on the EL. With the trend to multi-core CPUs, simulation servers with a larger number of CPU cores became widely available. In order to exploit the parallel computing capabilities of the hardware, the parallel paradigm has to be considered in the software implementation to exploit the hardware efficiently.

For executing the Modelica models of the BESs in parallel, a Parallel Execution Framework (PEF) has been developed which allows to execute C-Code generated from Modelica models in parallel. The development of an own framework was necessary as all available Modelica environments do not provide parallel execution capabilities. The development of the PEF followed the concepts known from computing science and are shortly introduced in the following paragraphs.

The general idea of parallelism on a software level is to split up the tasks of an application and let the hardware work on the subtasks in parallel. Ideally, a task which was split up once could be solved in half the time compared to the serial solution. However, the overall speed-up is less because the hardware needs time to split up the work, start working on it and again merge the partial solutions. Anyway, a parallelization of a software offers the possibility to speed up an application, especially if the hardware provides the infrastructure.

In general, the implementation of a software can apply parallel computing features by using processes or threads. A process is defined as an independent program which can be executed on its own. A process is provided with its own address space, memory and other resources by the operating system (OS). A thread is a part of a process and every process contains at least one thread.

By using more than one thread per process, the execution of the individual threads can be parallel executed within the process. Multiple threads which are part of the same process are sharing the same resources which can lead to issues and has to be considered during the implementation. In general, the different threads of a process need to share and exchange information with each other. The mechanism of exchanging can cause undefined behavior when different threads are simultaneously trying to access the same global resource thus it is important to synchronize the threads to avoid such situations. There are different solutions for the parallelization and synchronization of threads, some are provided directly by the OS, some can be used via the inclusion of libraries like OpenMP [67]. A process with only one thread cannot get synchronization problems because such a process is a linear running program with no parallel running parts. However, in order to exploit the parallel computing capabilities multiple processes can be executed in parallel. The data exchange among the different processes can be realized by a socket based communication which uses the server/client concept or by inter-process communication (IPC) methods which are provided by the OS. The IPC methods of the OS are in general much faster than a socket based solution.

Within the EL of the here presented simulation platform, the simulation of each BES model is executed within a separate process by the help of the IPC methods shared memory and messages. The reason for the process oriented approach instead of the thread based approach is that the model code exported from other modeling and simulation environments cannot guaranteed to be thread safe, thus applicable for the thread based approach.

Additionally to the parallel execution of the individual models, the PEF provides an automatic setup of the simulation as well as the data and time synchronization between the individual processes and the RTI and thus to the simulators within the other layers.

Network Layer (NL)

The function of the network layer is to perform the simulation of the energy supply networks within a city district energy system. The most relevant network is the electrical network, but also district heating networks and gas networks can be simulated within the NL. For the simulation of the energy supply networks powerful simulators are available. As those simulators are in general single-core applications, the parallelization within the network layer is limited to the parallel execution of the different networks in their specific simulator instance. For example, the electrical grid could be simulated in one simulator and the gas network in another simulator, assuming that there is no coupling between the networks besides at the BES which are simulated within the previously introduced EL.

System Control Layer (SCL)

System level control and energy management algorithms are implemented and simulated within the SCL of the simulation platform. Depending on the concept regarding the structure of the control and energy management system and algorithms, a different simulation tool most suitable for the specific requirements might be used. In general, the here presented simulation platform should provide sufficient flexibility regarding the integration of those tools in order to be able to investigate and compare different algorithms. The degree of parallelization within the SCL depends on the applied software tool and also the implemented algorithms. For example, MATLAB a popular tool for fast prototyping of control algorithms, which has been integrated in the simulation platform as a generic simulation tool, provides the possibility for parallel computing [68].

4.4.4 Implementation

Following the described approach in the previous section, the here presented simulation platform is composed of several different simulators. In order to provide data and time synchronization among the individual simulators an RTI is required. Here, a commercial RTI called TISC Suite by TLK Thermo has been used [69]. TISC Suite provides ready to use interfaces to commonly used simulators, like SimulationX [70], MATLAB or Dymola but also a C++ API which allows the integration of other simulators which themselves have a C++ API. The TISC Suite with its interfaces is implemented as a client/server architecture. The interfaces establish a TCP/IP connection to the TISC server which allows to distribute the whole simulation on different simulation servers. During the initialization of the connection between a client and the TISC server, the client registers the required input and output variables at the server. The variables can be of the type scalar, vector or matrix. During the simulation the client will provide updated values for the output variables and send them to the TISC server. Vice versa for the input variables, here the client expects updated values provided by the other simulators. The time synchronization is done by the exchange of signals: during the simulation when the output variables of a simulator are updated, the simulator will send a synchronization signal to the server and wait for a signal from the server. As soon as the TISC server has received the synchronization signals from all simulators, the server sends itself a synchronization signal to all the clients. On reception of this signal, the clients start requesting the required input variables from the server and will start the simulation of the next MTS. The following sections provide details on the implementation of the individual layers of the simulator as well as the individual interfaces to the TISC server.

Entity Layer

The main part of the EL is the Parallel Execution Framework (PEF) which coordinates the setup and execution of the simulation processes of the individual BES models as well the time and data

synchronization with the TISC server. The models themselves are provided as C-Code generated by Modelica modeling and simulation environment like SimulationX or Dymola.

PEF was developed in order to provide an automatic configuration of a parallel execution of a large number of BES models as well as the communication channels for data and time synchronization. In order to provide an automatic setup, the PEF reads first a settings file which contains the IP address and port of the TISC server as well as the start and end time of the simulation. A second input file provides specific information about the simulation scenario. Furthermore, the PEF can read further input data from files which can be provided as input for the simulation; e.g. like time series representing the electric power consumption of the BESs. The file describing the simulation scenario consists of a list of all BES instances and provides further data like the specific BES model, the number of their parameters, inputs and outputs as well as initial values for the inputs and the parameter values. For each entry in the scenario configuration file, the PEF creates an instance of a generic entity class. The instance starts a process with the corresponding model code. The communication between the instance of the entity and the corresponding model process is realized by messages and shared memory. In detail, the instance provides methods to write values to the shared memory and send a message to the model process. Those methods can be called by the main PEF process if new input data is available and a new MTS should be calculated. Vice versa, the model process writes output values after the calculation of a MTS to the shared memory and sends a message to the entity instance. The main PEF process collects the data from all instances and provides it to the other simulator via the TISC server.

In order to send data to simulators in other layers of the simulation platform, the PEF establishes a TCP/IP connection to the TISC server and registers for each BES instance a vector with the model outputs and the vectors with the model inputs. The general structure of the PEF is shown in Figure 4.22.

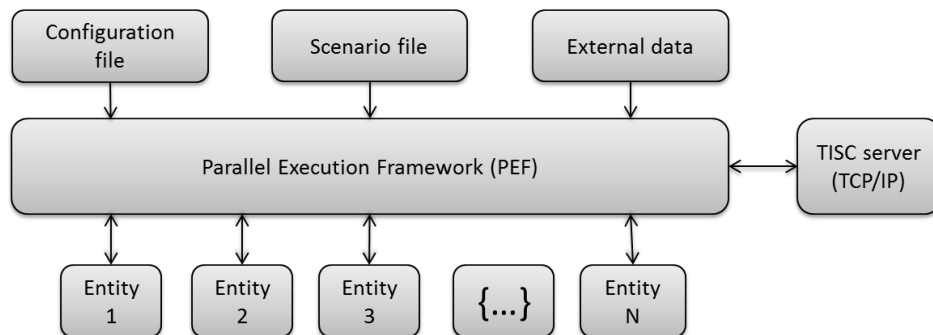


Figure 4.22: Schematic of the structure of the Parallel Execution framework (PEF)

Network Layer

For the simulation of the energy supply systems, here electrical grid, within the NL, the power system simulation tool Neplan from BCP has been chosen [71]. Besides the simulation of electrical networks, Neplan also supports the simulation of gas, thermal and water networks which are interesting features for a further extension of the here presented simulation platform. Neplan offers a C++ API which can be used for extending the simulation tool by custom code. The custom code will be compiled to a dynamic link library (DLL) which can be loaded and executed by Neplan. Here, functions have been implemented within the DLL to automatically setup the connection to the TISC server, request the required input data, executed a load flow calculation and send the resulting output values to the TISC server. Instead of Neplan other simulators could be integrated into the simulation platform, even different ones for different network types, e.g. district heating or gas network. The only requirement is that the simulator have a C++ API for the integration of the TISC interface.

System Control Layer

For the implementation of energy management algorithms within the SCL of the simulation platform, the TISC interface for Matlab/Simulink has been used. This interface as part of the TISC Suite allows the graphical setup of the interface via Simulink. Matlab/Simulink has been chosen as it is widely known and potential users of the simulation platform are already familiar with the tool. Furthermore, in a Simulink block Matlab source code can be easily integrated which provides sufficient flexibility to implement new algorithms or even interface further external tools, e.g. like a solver for optimization problems. As for the NL, also here, other simulators, e.g. a framework for the simulation of MAS, could be integrated instead of Matlab/Simulink.

4.4.5 Platform Integration

Despite the partitioning of the simulation of the system into subsystem corresponding to the introduced layers, the simulation has to yield results as of an unpartitioned system. Thus, the data flow and the synchronization of the different layers is introduced in the subsequent section, followed by an platform integration test. The focus of this section is to verify the proper function of the platform and not to verify the simulation models. The verification of the simulation models is shown in previous section 4.3.1.

Data Flow

As mentioned in section 4.4.3, the data and time synchronization among the different layers of the simulation platform can be configured in different ways. Here, as the simulation within the NL as

well as simulation of the algorithms within the SCL are discrete time simulation and only the simulation within the EL is a continuous time simulation, the data and time synchronization has been configured as shown in Figure 4.23. The set of variables mentioned in the following explanation of the data flow are only exemplary and can be extended or exchanged by other variables.

As shown in Figure 4.23, the simulator within the EL calculates the first MTS, passes the results to the TISC server, from which the NL requests the active and reactive power values. Those values of each BES are inserted in the corresponding load model within the grid model and a load flow calculation is executed. Then, the results of the load flow calculation, e.g. the voltage at each network node, are send to the TISC server. Finally, the SCL requests the required input data, comprising the data from the EL and NL, and performs the implemented system level control calculations. The output of those calculations is then made available via the TISC server for the calculation of the next MTS within the EL.

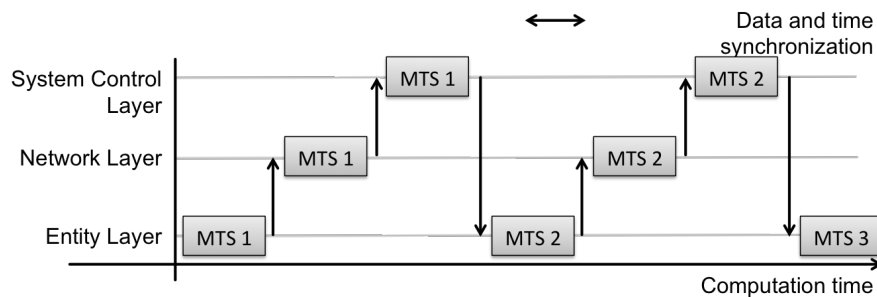


Figure 4.23: Implemented data and time synchronization

Verification of Model Integration into the Simulation Platform

The proper integration of the different layers of the presented simulation platform is demonstrated on a small example. The example is once simulated fully within a Modelica modeling and simulation environment and once on the simulation platform with a partitioning according to the different layers for the different subsystems. The simulation on the platform has been run twice with MTS of 3s and of 60s. The example consists of a feeder supplying three BESs. The first BES (BES1), closest to the supplying transformer, and the third one (BES3) are quipped with an EH while the second one (BES2) is equipped with a GB. The EH of the BES1 is turned on after 120s and the EH of BES3 is turned on after 60s. Figure 4.22 shows the resulting voltage at the point of common coupling (PCC) of BES3 and the feeder, the power consumption of the EH supplied by the grid as well as the SoC of the thermal storage of the BES. It can be seen that the power consumption of BES3 raises after 60s as the heater is turned on. Furthermore, the SoC raises and the voltage at the PCC drops due to the power flow at the feeder. The voltage drop at the PCC of BES3 after 120s is due to the startup of the EH in BES1.

The previously described results as shown in 4.22 demonstrate that the partitioning of the system

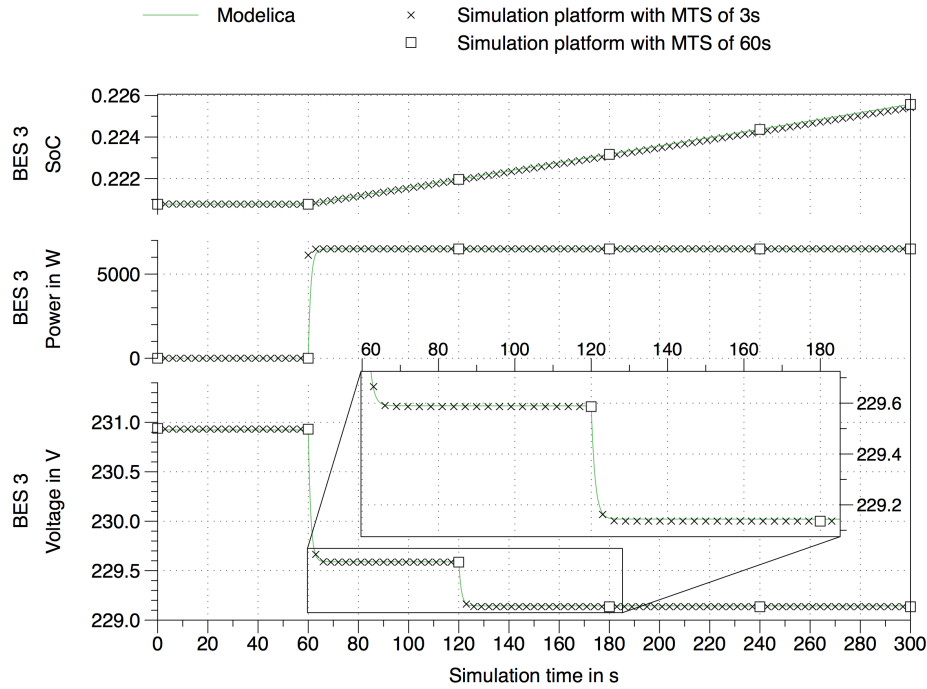


Figure 4.24: Voltage at PCC, Power consumption and SoC of BES 3 as results of a pure Modelica simulation and a simulation on the presented simulation platform with MTSs of 3s and 60s

into the subsystems according to the layers of the simulation platform does not have an impact on the simulation results. The exemplary shown curves as results of the pure Modelica simulation as well as simulation on the simulation platform with MTS of 3s and 60 s are perfectly aligned. However, it has to be noted that at the simulation platform the values of the coupling variables are only available at the synchronization time steps. Thus information about dynamic behavior in between two MTS is not available within the other layers and thus cannot be processed.

4.4.6 Performance of the Simulation Platform

The simulation of the reference scenario comprising only BESs with gas boilers and electrical heaters has been performed in order to demonstrate the performance of the developed simulation platform. Figure 4.25 and figure 4.26 show exemplary some variables resulting from the simulation. The purpose of those results is to show that the simulation platform is capable to execute large scale scenarios and deliver variables which are required to test energy management algorithms.

Figure 4.25 shows the active, reactive power as well as the secondary voltage at one transformer in the analyzed city district energy system.

Figure 4.26 shows exemplary some internal variables of one BES of the city district energy system.



Figure 4.25: Active and reactive power flow as well as secondary voltage at a transformer (T25) of the model of the city district energy system for a time period of 16 days for the reference scenario

The internal control algorithm turns on the heating system in order to keep the SoC in a certain range. Furthermore, the overall power consumption comprising the heating system as well as the time series representing the appliances and light of this specific BES is shown.

For the analysis of the computational performance of the simulation platform, the reference scenario has been simulated including the EL and the NL. The SCL has not been included in the simulation as the reference scenario does not comprise a system control level with energy management algorithms. Furthermore, the computation time of different energy management algorithms might vary significantly and thus might give not the correct picture of the performance of the platform. The execution of this reference simulation scenario comprising 752 BES took 10:55h while the computation time of the EL was 3:42h and of the NL was 5:22h. The sum of the computation times of the individual layers results in 9:03h. Thus, the difference between overall runtime and the computation time of the layers is 1:52h. This additional runtime is due to the data exchange between the simulators.

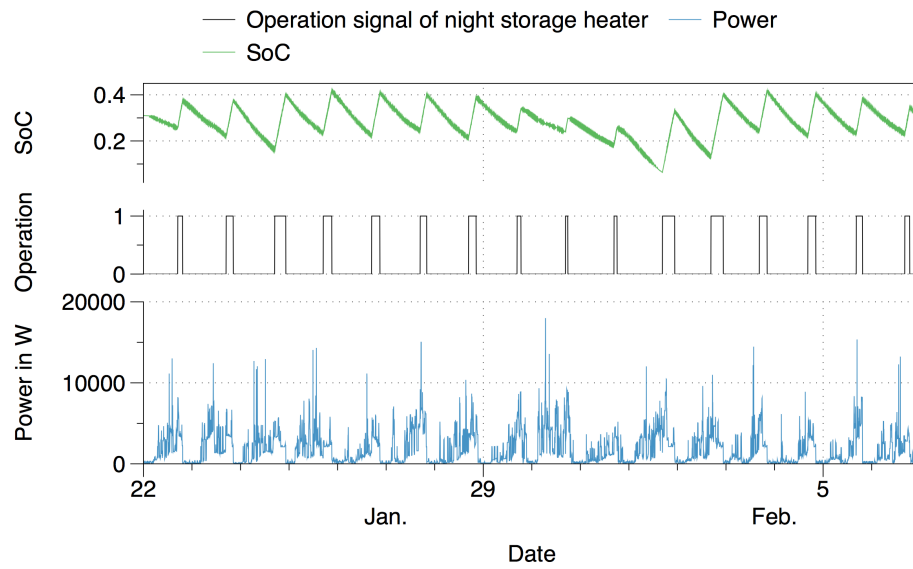


Figure 4.26: Power consumption, operation signal and SoC of an exemplary BES (ABS 21)

5 2DSM Operation

5.1 Introduction

The major outcome of 2DSM is a control approach for residential heating systems mainly HPs and μ CHPs. These units are combined with thermal storage systems to allow time-flexible operation.

The 2DSM control strategy consists of two phases: a scheduling phase for day-ahead planning and a short-term phase, in which schedule deviations and RES variations are compensated.

Within the planning phase, the thermal and electrical demands are forecasted and used to schedule the operation of the heating systems while satisfying the technical constraints of the heating systems as well as the voltage thresholds in the distribution grid. The objective for the scheduling is to maximize integration of RESs. The generated schedules for the next day are passed to the short-term compensation algorithm. The short-term balancing algorithm has two function: First, the execution of the schedules during the day and second the handling of deviations from the forecasted behavior caused by resident's behavior or short-term forecast updates. The short-term control calculates the state of the system, the status and availability of the devices and assigns dispatchable resources to compensate deviations.

Section 5.2 presents the forecasting methods for the electrical and thermal demand. A detailed analysis and classification of possible deviations is presented in section 5.3. The scheduling model is introduced in the section 5.4. Finally, the short-term balancing is shown in section 5.5.

5.2 Load Forecasting

In the scheduling phase, the distributed energy resources are coordinated to achieve a common target while satisfying the forecasted electrical and thermal demands of the dwellings.

5.2.1 Electrical Demand Forecast

The forecast of the electrical loads i.e. appliances, lights and domestic hot water, is an essential input for the scheduling phases. Depending on the coordination scheme, the forecast can be computed for a cluster of buildings either individually or combined. The combined electrical load of a multi-apartment building or buildings' cluster is relatively smooth, which is rather easier to forecast compared to the forecast of individual load profiles which are typically characterized by

unpredictable patterns as shown in Figure 5.1. Therefore, in 2DSM a cluster forecast approach is implemented.

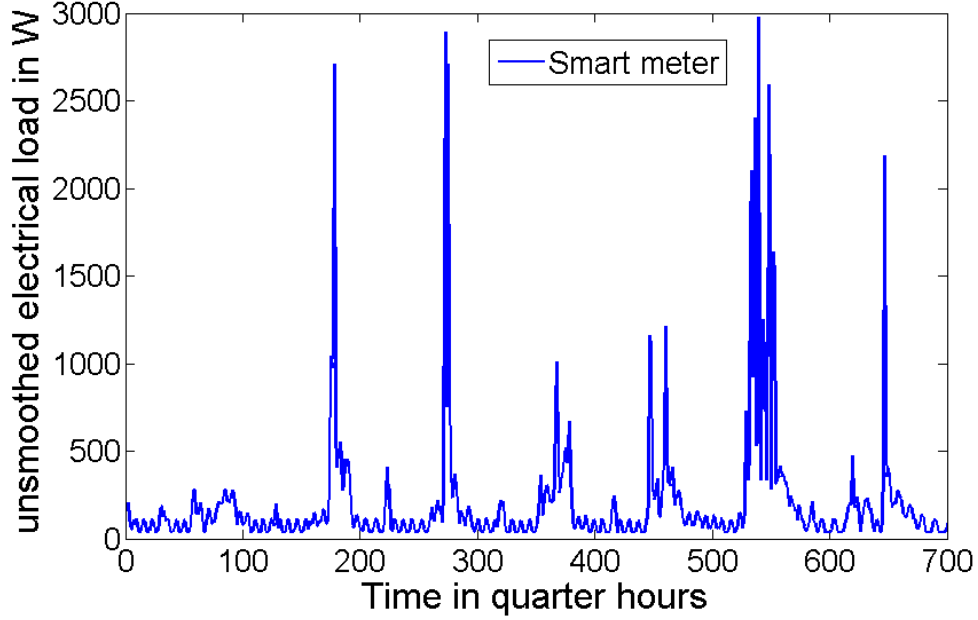


Figure 5.1: Example of an individual electrical demand profile

Literature Review

Electrical load forecasts are widely used by energy suppliers, grid operator and energy markets. Over the years, several electrical demand forecasting models have been investigated. They are based on a variety of techniques such as regression, multiple regression, exponential smoothing, adaptive load forecasting, stochastic time series- auto-regressive, ARMA model, ARIMA model, genetic algorithms, fuzzy logic, neural networks and hybrid methods. Several studies provide a general overview of the different forecasting methods ([72], [73]). These forecasts can be broadly classified in 2 categories: short term forecast and long term forecast. Since the planning horizon for the scheduling in 2DSM is one day ahead, a short term forecast is required.

In [74], the authors compare several forecasting methods: an exponential smoothing model based on the additive Holt-Winters method, an ARIMA model and an ANN. The authors apply these algorithms to compute short-term forecasts for 24 hours ahead. The results indicate that the exponential smoothing approach with two seasonalities outperforms more complex methods like the ANN or ARIMA models. Therefore, the Holt-Winters approach with two seasonalities is adopted in our work.

Electrical Demand Forecast Algorithm

The additive Holt-Winters model assumes that the measured value can be decomposed into the sum of a level (l_t), a linear trend component (b_t) and a seasonal term (s_t).

The additive Holt-Winters model can be written as follows [75]:

$$f_t(k) = l_t + k \cdot b_t + s_{t-s_1+k} \quad (5.1)$$

$$l_t = \lambda \cdot (y_t - s_{t-s_1}) + (1 - \lambda) \cdot (l_{t-1} + b_{t-1}) \quad (5.2)$$

$$b_t = \theta \cdot (l_t - l_{t-1}) + (1 - \theta) \cdot b_{t-1} \quad (5.3)$$

$$s_t = \gamma \cdot (y_t - l_{t-1} - b_{t-1}) + (1 - \gamma) \cdot s_{t-s_1} \quad (5.4)$$

In this set of equations, $f_t(k)$ denotes the forecast for the k^{th} time step, which is a prediction of y_{t+k} . The variable s_1 represents the length of the seasonality. The smoothing parameters are λ , θ and γ . Their values are positive and less than or equal to one.

Taylor [76] further developed the standard Holt-Winters model by introducing a double and triple seasonal approach. These multiple seasonalities take into account the daily, weekly and annual changes of the electrical demand. Since the large amount of data needed to consider the yearly seasonality requires large storage and is hardly available, the double seasonal model is used in 2DSM. The implemented forecasting technique combines the model formulated by Taylor [76] which comprises the equations 5.5 to 5.8 with an simulated annealing algorithm to adaptively optimize the smoothing parameters and consequently improve the forecast's accuracy.

$$f_t(k) = l_t + d_{t-s_1+k} + w_{t-s_2+k} + \phi^k \cdot (y_t - l_{t-1} - d_{t-s_1} - w_{t-s_2}) \quad (5.5)$$

$$l_t = \lambda \cdot (y_t - d_{t-s_1} - w_{t-s_2}) + (1 - \lambda) \cdot l_{t-1} \quad (5.6)$$

$$d_t = \delta \cdot (y_t - l_{t-1} - w_{t-s_2}) + (1 - \delta) \cdot d_{t-s_1} \quad (5.7)$$

$$w_t = \omega \cdot (y_t - l_{t-1} - d_{t-s_1}) + (1 - \omega) \cdot w_{t-s_2} \quad (5.8)$$

In this formulation, d_t and w_t indicate the daily and the weekly cycle. The variables s_1 and s_2 represent the lengths of these cycles. The time stamp of the forecast is set to 15 minutes, the length of the daily cycle therefore becomes $s_1 = 24 \cdot 4 = 96$ and the length of weekly cycle results in $s_2 = 7 \cdot s_1 = 672$ time steps. The smoothing parameters are ϕ , λ , δ and ω . The values of these parameters are again between zero and one. In equation 5.5, the term involving the smoothing parameter ϕ is an adjustment for first-order error auto-correlation. According to Taylor, "this adjustment substantially improves the performance of the Holt-Winters method" [76]. The trend term is not included in this formulation. According to Taylor, the trend term does not change the forecast accuracy [76].

All values, but the smoothing parameters are initialized to zero. The smoothing parameters are initialized to 0,5 and are optimized before each new forecast using simulated annealing on the basis of the previous week's demand.

Simulated Annealing

Simulated annealing is a metaheuristic for global optimization problems, which uses a random driven search technique [77]. It is a computational analogy to the annealing process of metals, during which hot metal cools and freezes into a crystalline state. During this annealing process each particle pursues a state of minimal temperature. This situation can be modeled as follows: If the temperature of a neighboring particle is lower than the particle's current temperature, a transition towards the lower temperature will take place with certainty, but if the neighboring particle has a higher temperature, a transition will only occur along a stochastic distribution [78]. In a converged stage, all elements will have their minimal temperature which means that the hot metal has reached a crystalline state.

The algorithm is similar to local search [78], except that it does not only accept improvements of the objective function, but also a worsening with a probability p . This feature is necessary to escape from local optima, when searching the global optimum. The probability for accepting set-backs is defined as follows, based on [78]:

$$p = \exp\left(-\frac{z(x_{n,j}) - z(x)}{T_j}\right) \quad (5.9)$$

In this equation $z(x_{n,j})$ denotes the value of the objective function of the currently investigated neighbor in iteration j , which is the SSE value of the forecast. The current solution vector is indicated by x and T_j stands for the so called temperature. The temperature is updated with $T_{j+1} = 0,9 \cdot T_j$ and initialized as $T_0 = 0,01 \cdot z(x_0)$, with $z(x_0)$ as the SSE value of the initial guess. As initial guess all smoothing parameters are assumed to be equal to 0,5.

The algorithm can be written as follows [79]:

1. Initialization
 - 1a. Set starting temperature: $T_0 = 0,01 \cdot z(x_0)$
 - 1b. Reset iteration counter: $j = 0$
2. Repeat until $j = j_{\max}$
 - 2a. Generate N random neighbors of the current solution as

$$x_{n,j}^i = \min\left\{\left|x^i + 0,2 \cdot \frac{\text{random} - 0,5}{1 + 0,3 \cdot t}\right|; 1\right\} \quad \forall n = 1..N$$
 - 2b. For all n : If $[(z(x_{n,j}) < z(x)) \text{ or } (\text{random} < p)]$ then set $x = x_j$
 - 2c. Update temperature: $T_{j+1} = 0,9 \cdot T_j$
 - 2d. Increase iteration counter: $j = j + 1$

In this algorithm, *random* stands for a randomly drawn number between zero and one. The neighborhood is defined in step 2a. $x_{n,j}^i$ denotes the i^{th} component of the n^{th} neighbor of the current solution x . Apparently, this definition satisfies the aforementioned constraint: $0 \leq x_{n,j}^i \leq 1, \forall i$. Also this definition ensures that the neighborhood becomes more concentrated at higher steps, which is necessary to approach the optimum [78].

Exemplary Forecasting Results

The performance of the algorithm is assessed by forecasting the aggregated electrical demand profile of 34 houses from the Lucas Cranach street for one year. The individual consumption profiles are estimated by making use of the electrical standard load profile (SLP) from North Rhine-Westphalia [80]. This profile data is collected and processed annually for several regions; SLP is normalized with a cumulative demand of 1000 kWh. Therefore, this profile must be scaled with accordance to the number of residents

Figure 5.2 depicts the forecasting results of random 7 consecutive days of the one year forecast.

The Mean Absolute Percentage Error (MAPE) indicator, defined in 5.11, is used as an indicator of the forecasting accuracy. The forecasting error (e_i) is computed as the difference between the real observation (y_i) and its forecast (f_i).

$$e_i = y_i - f_i \quad (5.10)$$

$$\text{MAPE} = \frac{100\%}{n} \cdot \sum_{i=1}^n \left| \frac{e_i}{y_i} \right| \quad (5.11)$$

The MAPE value of the one year forecast is 10.15 %. When computing the MAPE for every day separately, the median error of this series is then 5.32 %.

5.2.2 Heat Demand Forecast

The thermal demand forecast of the buildings represents another constraint for the coordination. This forecast ensures that the comfort standards of the residents are met during the scheduling phase. Unlike the electrical demand which can be made available globally from different resources, the heating load is met locally on building level. A connection to a heating network is not considered.

A common approach used for forecasting thermal loads is artificial neural networks [81]. However, this method requires a large amount of historical data for training the neurons as well as a high

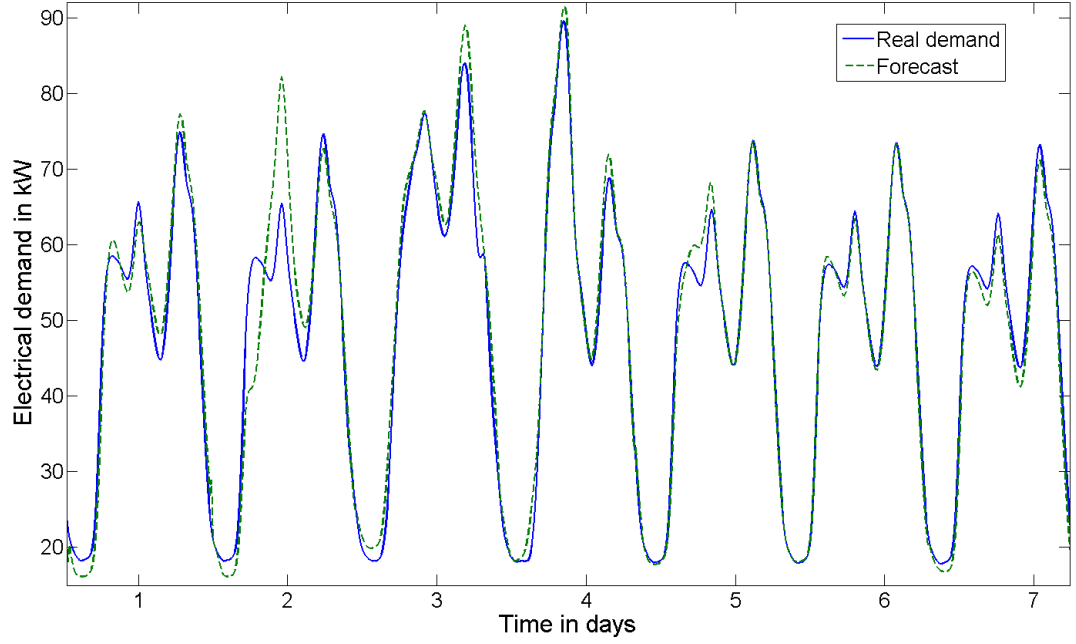


Figure 5.2: Electrical load forecast for 7 days

computational effort. We propose a time-series based Separation Algorithm (SA) for thermal demand forecast which is characterized by an adaptive approach that requires two inputs, a forecast of the outdoor temperature and the thermal demand measurement data of the past day.

The algorithm separates the heat demand into a systematic and a behavioral component. The systematic component is determined by computing a heating curve which correlates the heat demand to the outdoor temperature. This is established due to evident dependency of the heating demand on the weather conditions and mainly the outdoor temperature. The behavioral component is derived from computing a forecast of the previously measured heat demands. This comprises the measurement of the past day as well as the corresponding day of the previous week. Consequently, SA requires a small database and low computational effort, which enables a direct implementation on conventional embedded systems in future smart homes.

Description of the Algorithm

The SA receives the outside temperature for the upcoming day and the heat demand for the previous day as input data. This input is used to separate the heat demand into a physical component that only depends on the outside temperature and a behavioral component that represents the user's habits. The behavioral component, which will be referred to as seasonality, is extracted from previous heat demand measurements.

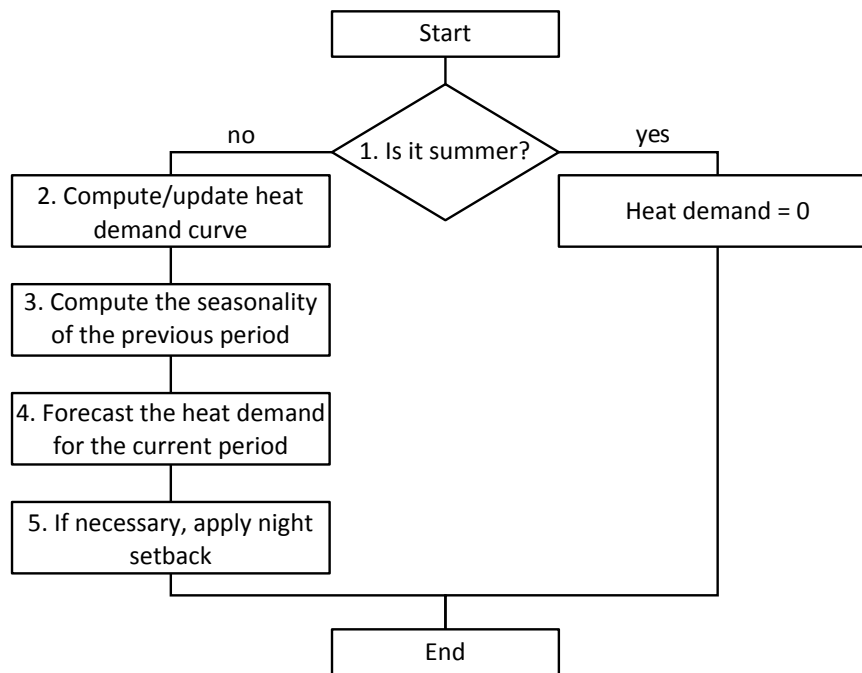


Figure 5.3: Flow chart of the algorithm steps [79]

Figure 5.3 displays the flow chart of the algorithm. The first step determines whether or not it is reasonable to turn on the heating device in the upcoming period. Empirically, a threshold of 16°C for the mean temperature and 20°C for the peak temperature are implemented. If today's or yesterday's temperature distribution exceeds one of these thresholds, the heat demand is set to zero. Both today's and yesterday's temperature distribution are considered, to dampen the effects of short-term temperature drops. If the heat demand is not set to constant zero, the Heat Demand Curve (HDC) is computed; afterwards yesterday's seasonality is extracted. The subsequent step is the actual forecast, which is finally followed by a review that takes into account a possible night setback. In step 2, HDC represents the functional relationship between the outside temperature and the corresponding heat demand. The design is inspired from the heat curve, which is commonly used in heating systems and expresses a functional relationship between the outside temperature and the feed temperature of the heating circuit. In order to enable SA to adapt to sudden changes in the outside temperature, the HDC is a linear regression of the previous day's (temperature/heat demand) couples as well as a *restriction*. The latter depicts an upper limit for heating and is empirically chosen *at the outdoor temperature of 20°C , at which the heating is assumed to be zero*. Using more input data than the past day's for the regression leads to over fitting and worsening of the forecast's accuracy. Higher-order regression curves worsen the forecast as well, because the HDC becomes less reliable outside of the input-temperature-interval range.

For extracting the seasonality from the previous period, yesterday's forecast is recomputed by using the yesterday's outdoor temperature as input data. The result is then smoothed by using a moving

average scheme and subtracted from the corresponding measured heat demand. This represents the difference between the systematic forecast and the actual demand and consequently yesterday's seasonality. Every day's seasonality is stored in a vector with 96 entries, one for each time step. It is necessary to execute a moving average, which is presented in equation 5.12, after using the HDC to dampen the effects of sudden temperature changes. Since buildings possess a significant heat capacity, short-term fluctuations in the outside temperature are not likely to affect the heat demand in the same abrupt manner. In the equation 5.12, $\bar{y}(t)$ denotes the averaged value at time step t and $y(t)$ the value before averaging. At $t = 0$, resp. $t = t_{\max}$ the centered formulation is changed to a forward, resp. backward scheme, maintaining three points for the averaging.

$$\bar{y}(t) = \frac{y(t-1) + y(t) + y(t+1)}{3} \quad (5.12)$$

After extracting yesterday's seasonality, today's predicted outdoor temperature is used as input for the HDC to obtain a forecast for the upcoming day $f(t)$, only considering the systematic component. Subsequently, today's seasonality is determined as a linear combination of yesterday's and the equivalent day of the previous week's seasonality, as shown in 5.13.

$$s(t) = s(t-1) \cdot x + s(t-7) \cdot (1-x) \quad (5.13)$$

In this equation x denotes a weighting parameter, with $0 \leq x \leq 1$. This parameter is calculated by choosing $x \in \{0; 0,1; 0,2 \dots 0,8; 0,9; 1\}$ that minimizes the Sum of Squared Error (SSE) of the past seven days. Today's seasonality $s(t)$ is then added to the systematic component of the prediction. The forecast is then determined by making use of the maximum function as indicated in equation 5.14, since the heat demand is always positive and $s(t)$ can be negative.

$$F(t) = \max\{f(t) + s(t); 0\} \quad (5.14)$$

In the final step, the algorithm looks for the time steps in which yesterday's heat demand is forecasted positively, but the actual demand was zero. The values are summed for the past week and stored. If these time steps recur during the same interval with an empirical likelihood, it is likely that there is a scheduled night setback. Accordingly, the time steps values of the forecast which fulfill this condition are set to zero while the others remain unchanged.

Performance and Results

The execution of the algorithm was tested using the input data from the simulation of the building model introduced in chapter 4 and assuming a perfect outdoor temperature forecast.

Figure 5.4 displays the systematic and behavioral components of the forecast. The continuous line depicts the simulation data which represent the measured heat demand, the dashed line shows the

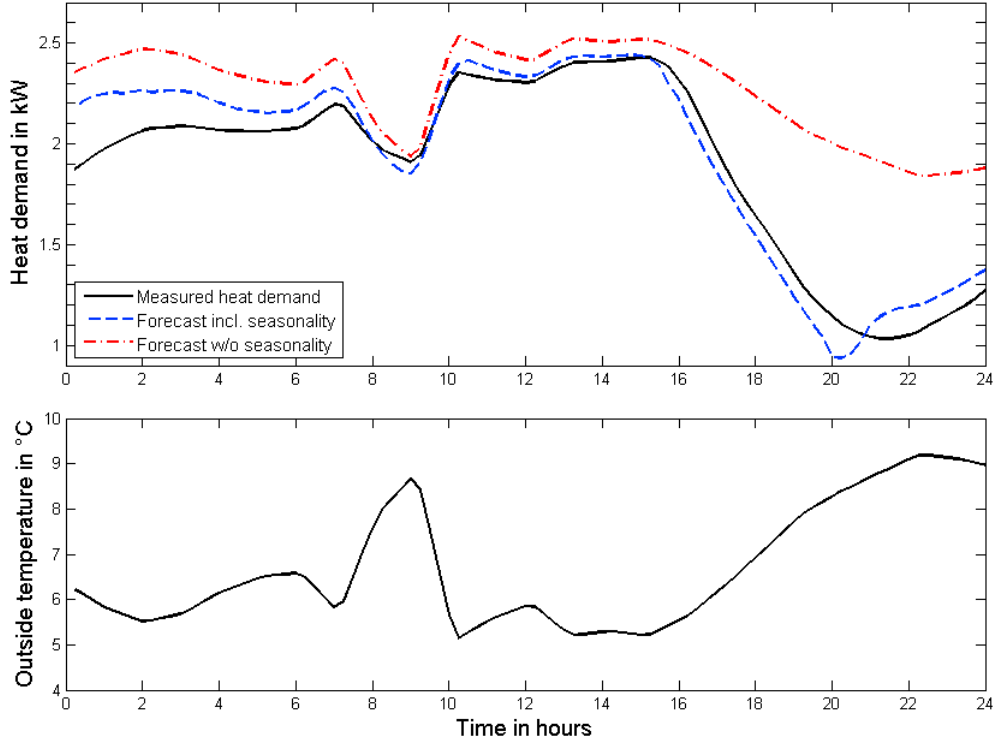


Figure 5.4: Illustration of the seasonality influence in the forecasting algorithm

forecast after the seasonality has been added and the dashed-and-dotted line depicts the systematic component. The latter depends on the outside temperature only; therefore the dashed-and-dotted line predicts the same heat demand at hours 9 and 21, because the outside temperature is nearly identical. As shown in this figure, the real heat demand drops significantly at the hour 21, which is anticipated by the behavioral component. Apparently, the seasonality corrects the systematic component towards the real heat demand and is so able to anticipate a reduced heat demand after the hour 16.

The performance of the SA is evaluated by comparing the forecast results for a one year period with an ANN model for 4 different heat demand sets representing different building insulation classes. The ANN is composed as a Nonlinear AutorRegressive eXogenous (NARX) model with the ambient temperature as exogenous input and comprises 20 neurons.

The results are listed in table 5.1 and show that SA outperforms the ANN in terms of forecasting accuracy. The error indicator, Mean Average Scaled Error (MASE) suggested in [82] is used. The MASE indicator, displayed in equation 5.15, compares the forecasting error e_t with the error generated by the naïve, one step forecast ($|y_i - y_{i-1}|$). The forecasting error is defined as the difference between the real heat demand and the prediction.

$$\text{MASE} = \frac{\sum_{t=1}^n |e_t|}{\frac{n}{n-1} \cdot \sum_{i=2}^n |y_i - y_{i-1}|} \quad (5.15)$$

Method	Set 1	Set 2	Set 3	Set 4
ANN	13.539	4.381	3.974	28.411
SA	9.898	3.481	2.132	9.968

Table 5.1: Forecasting results of the separation algorithm and ANN

However, the accuracy of forecasts is always limited. Even marginal forecast errors and deviations can sum up over time and lead to unforeseen scenarios due to the changed conditions. As in the presented energy management algorithm the scheduling is done one day ahead in resolution of one hour, the operation of the system has to be monitored in real time. Therefore, the possible deviations from the agreed schedules due to user behavior and short-term weather changes were analyzed and evaluated in detail within the project 2DSM. The results are presented in the following.

5.3 Analysis and Classification of Forecast Deviations

In this section, the analysis and classification of short-term variations in the load profile of residential buildings is introduced, based on a study presented in [83]. The study provides a detailed analysis of the deviations from a reference load profile for thirty residential buildings, which may be used for various monitoring and control purposes in the development of solutions and concepts for Smart Grids. Methods for statistical analysis were used to identify and classify different kinds of anomalies in the energy consumption curve, enabling the automation of appropriate control strategies.

Beside the methods for statistical analysis used to evaluate the load profile variations, the section contains the classification of deviations according to the time of the day, the day of the week and the season. Furthermore, PV is introduced as a potential source for deviations. The study on variations of residential load profiles includes also a link between the range of deviations and dispatchable resources for their compensation.

5.3.1 Background

As already addressed in sections 5.1 and 5.4, the 2DSM control strategy is organized in two phases, a day-ahead scheduling and a short-term phase for the compensation of deviations from the negotiated schedules.

The short-term compensation is explained in detail in section 5.5. Here, the main principles are summarized in order to motivate the deviation study presented in this section. They are illustrated in 5.5.

The energy management algorithms are not directly dependent on the control architecture, as the information exchange and the decision making instances are not essential parts of the algorithms. However, the short-term compensation algorithm is illustrated as implemented within the sample architecture of an agent control platform with hierarchical structure. The control structure is based on low-level agents, which are building or household agents, and higher-level aggregator agents, operating at substation level and higher.

The building and aggregator agents monitor the system in order to detect changes in the conditions, which are used to forecast the demand and generation profiles. These are for example the weather and residents' behavior. Deviations can be detected by the domestic energy management system which tracks the energy demand and residents' presence, and by the aggregator agent updating weather forecast for bigger regional energy generation sources, which indicate possible deviations from the schedule. In this case, adequate compensation actions are triggered according to the flexibility of the household, the character of the deviation and the aggregated deviation.

Based on information from the system monitoring and the building agents, the aggregator agent evaluates the aggregated deviation and the cluster flexibility. In this process, precise information about the character of the deviations is necessary, in order to take adequate control actions. Therefore, in the study, deviations are analyzed with respect to their magnitude, duration and frequency of occurrence.

The study of deviations comprises two options regarding the amount of data which are collected. One option is to apply statistical process control methods to detect occurring deviations during run time. As the control methods are based on statistical analysis, they offer a compromise between accuracy and data requirements. Highly automated buildings and local intelligence could be able in future to detect and provide information on expected and occurred deviations based on learning algorithms. However, especially in residential areas, the current and near-future level of building automation is rather low. In this case, a continuous measurement of the energy consumption can be used as an input for a personalized Statistical Process Control (SPC) chart for the detection of deviations from the load profile, which is statistically expected for the household according to the number of residents and the current time.

The second option for the analysis of deviations is the use of deviation categories in order to evaluate occurred deviations and make assumptions on their characteristics such as duration, magnitude, etc. This feature is beneficial both for areas with good and with limited to no monitoring or metering possibilities at all. In areas with broad metering possibilities, which provide detailed information about the current operation status, the deviation categorization enables an accurate evaluation of the detected variations. In areas with limited to no metering or monitoring possibil-

ities, the deviation categories help to make assumptions on the frequency of occurrence, magnitude and duration of deviations. Using this method, sample deviation categories are defined based on real data. The categorization of deviations was done based on high-resolution, fine-granularity measurement data from the load profiles of thirty residential buildings in Upper Austria, gathered within the project “ADRES CONCEPT” [84].

The use of simple process control charts, such as the Shewhart chart, can help in classifying load deviations by identifying the intervals when they usually occur, as well as the duration and magnitude of such deviations in a group of households, in order to design adequate control or compensation schemes. Given the monitoring nature of the SPC charts, they can be incorporated in the operation process in order to detect significant load disturbances, possibly pointing to uncontrollable or external variables, and trigger the compensation mechanism. Therefore, SPC charts can support and complement the building automated load control.

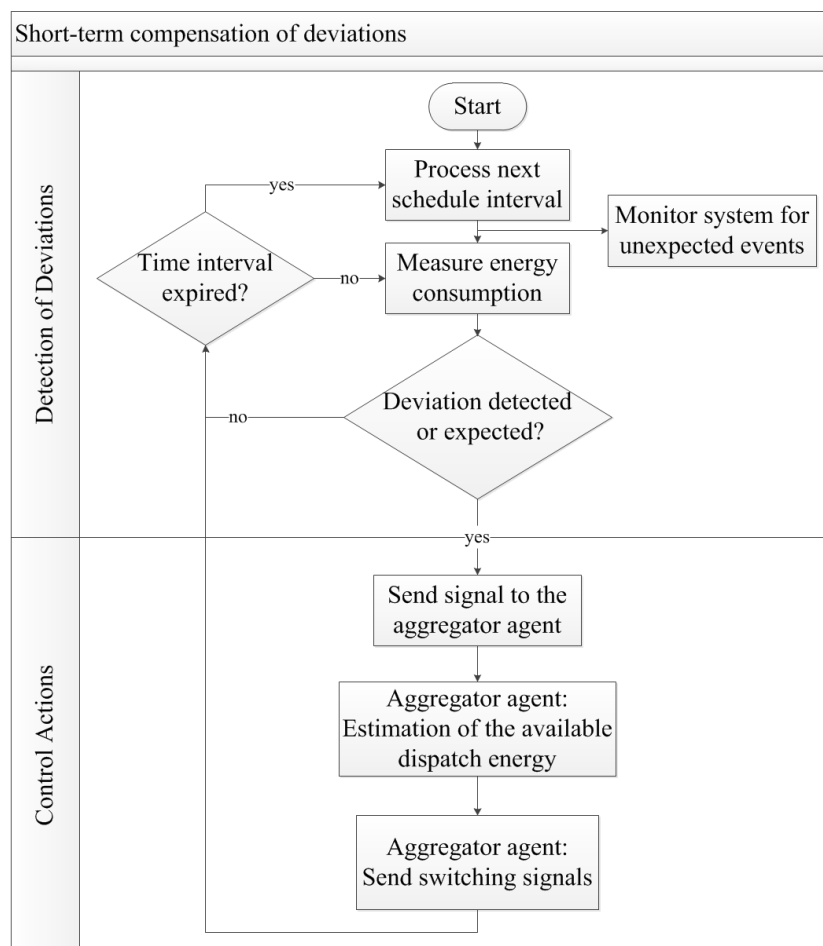


Figure 5.5: Procedure for the short-term detection and compensation of deviations

5.3.2 Methodology

In the following, the methods for the evaluation and classification of occurrence of deviations in the load profile of a group of residential buildings are presented.

Data Background

The studied data were generated in the research project “ADRES-CONCEPT” [84] and contain the load profiles of thirty households in Upper Austria, during one week in summer and one week in winter time. The dataset contains values of active power, reactive power and voltage per phase, for each household, in time resolution of one second. For the study, load profiles are calculated with the three phase power value per household.

Data Analysis

Forecasts and SLP are often employed by DR and DSM programs to manage the operation of shiftable loads such as domestic devices and storage units [85]. Advanced measurement units such as smart meters and elaborated forecast algorithms can provide more detailed and more precise load profile data which can be used for planning purposes. However, deviations from the forecast cannot be avoided. In fact, unpredictable and uncontrollable external variables such as solar irradiation and ambient temperature bring additional uncertainty and increase the forecast error. In order to keep processes and trends in certain limits and guarantee the stable operation of the power system, forecast errors have to be monitored and compensated for, if needed.

There are several options to deal with disturbances such as forecast errors and schedule deviations at control level. For the study of deviations, SPC and Automatic Process Control (APC) came into consideration. To understand the choice of a method, it is important to highlight the difference between process monitoring and process adjustment. SPC and APC are two complementary approaches used for process control. SPC clears forecast errors through process monitoring, while APC targets their compensation while adjusting the process. Within the short-term compensation of schedule deviations, this corresponds to the upper part of Figure 5.5. Common tool for process monitoring are control charts. For APC and process adjustment, different types of feed-forward and feedback control schemes are used for process adjustment.

For the deviation study, SPC was chosen to detect significant deviations in the process mean [86], [87], [88]. Two kinds of the mentioned control charts were applied to assess their suitability for the analysis of the residential load profile data provided by the project ADRES CONCEPT and for the support of the short-term compensation of deviations in 2DSM. These are the Shewhart chart, used as an exploratory data analysis tool for detecting large shifts in the process mean [89], and the

Roberts' exponentially weighted moving average (EWMA) chart [90], which is able to capture both large deviations over a short period of time, as well as small deviations in a long period of time.

In the Shewhart control chart, the sample mean is used as a center line (CL) of the monitored variable or process; the upper control limit (UCL) and the lower control limit (LCL) are calculated and plotted around the mean μ using the sample standard deviation σ according to equations 5.16 and 5.17, where n is the sample size, and k is a positive constant, which represents the probability that a value falls outside of the control lines given that the process is actually under control (i.e., for $k = 3$, 99.74 % of the values falls inside of the limits when the process is under stable operation) [89]. The control chart enables the continuous monitoring of the load profile and the detection of significant deviations which could affect the operation.

$$\text{UCL} = \mu + \frac{k}{\sqrt{n}}\sigma \quad (5.16)$$

$$\text{LCL} = \mu - \frac{k}{\sqrt{n}}\sigma \quad (5.17)$$

5.3.3 Classification of Deviations

As a basis for the analysis of deviation the German SLP was used. It is applied by Austrian utilities too, due to the good fit to the behavior of Austrian customers according to the cultural and geographical proximity. The SLP was scaled to the weekly consumption of the thirty households and fits the load profile very well.

Figures 5.6 and 5.7 illustrate the Shewhart control charts for all households and the scaled SLP (dashed line) for three days in the summer and winter week. The detected deviations are marked with a red circle. The UCL serves as the upper deviation threshold; there are no deviations below the LCL.

As expected, the character of the deviations, magnitude and duration, depend strongly on the observed time interval [87]. Due to the stochastic nature of human behavior, deviations, more numerous and with higher magnitude, are more likely when residents are present and active, this is mostly on mornings and evenings on weekdays. On weekends, due to the different behavior patterns, deviations are concentrated between late in the morning and late afternoon.

In particular, the study shows that day-time deviations occur on weekdays more frequently and with higher magnitudes in the interval between 17:30 and 22:00. On the weekend, the significant deviations are in the interval between 9:00 and 16:00. The results scaled down for 1000 kWh annual energy consumption are listed in table 5.2.

The analysis of the summer week identified significantly higher number of deviations (over 150) compared to the winter week (ca. 50). On weekends the number of deviations is similar for the

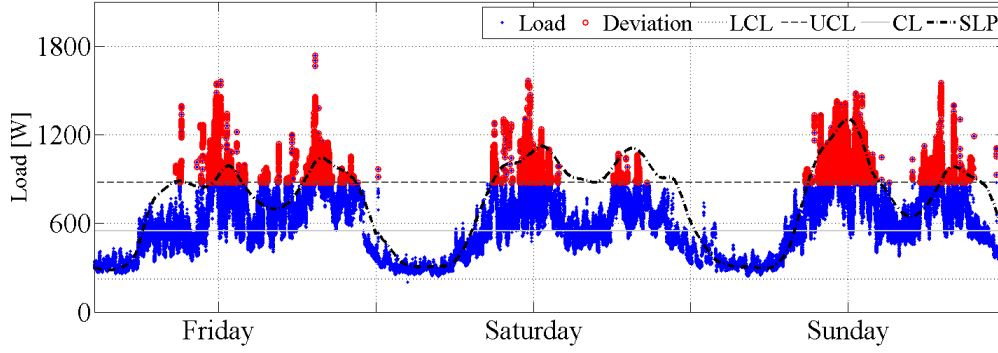


Figure 5.6: Shewhart control chart of the detected deviations for all thirty households for three days in the summer week

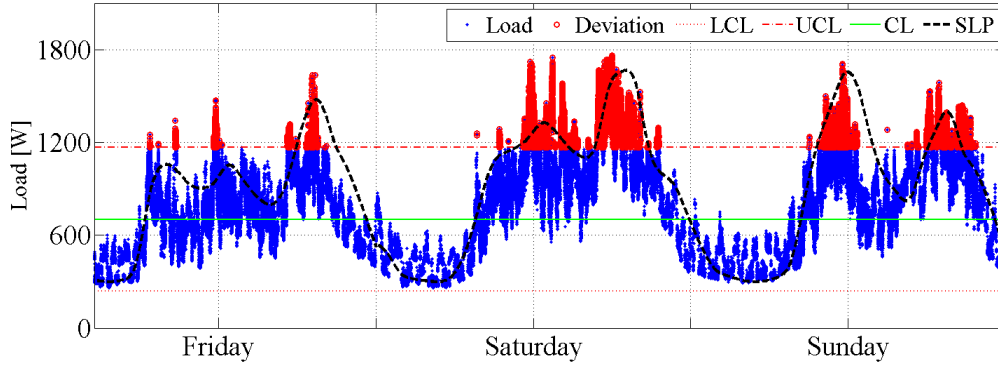


Figure 5.7: Shewhart control chart of the detected deviations for all thirty households for three days in the winter week

summer and for the winter periods, but significantly higher than for weekdays (ca. 40). The reason could be the more active behavior of residents in summer and on weekends. However, this could not be verified due to the limited amount of data. Therefore, at this point, a definite statement cannot be made. The majority of detected deviations have durations of less than 15 minutes.

The frequency of occurrence of deviations, their magnitude and duration are critical for the planning of adequate compensation actions within the short-term phase of the control strategy described in section 5.5. They are used as a benchmark to define the trigger intervals and to assign dispatch resources to compensate them.

5.3.4 Variability of PV Generation

PV is the most popular energy source installed in private residential buildings. There are numerous factors influencing the PV performance and adding variability to the generation curve: position of

Table 5.2: Categorization of the detected deviations scaled to annual consumption of 1000 kWh

Time interval	Weekday			
	Summer		Winter	
	Magnitude	Duration	Magnitude	Duration
7:30 a.m. – 9:30 a.m.	up to 25 W	up to 20 min	up to 35 W	up to 15 min
11:30 a.m. – 2:30 p.m.	up to 50 W	15 – 45 min	up to 60 W	15 – 35 min
5:30 p.m. – 10:00 p.m.	up to 85 W	45 – 90 min	up to 85 W	30 – 70 min
	Saturday			
	Summer		Winter	
	Magnitude	Duration	Magnitude	Duration
10:00 a.m. – 12:00 p.m.	up to 40 W	up to 45 min	up to 20 W	up to 20 min
12:30 p.m. – 4:00 p.m.	up to 110 W	20 – 60 min	up to 100 W	20 – 60 min
7:30 p.m. – 10:00 p.m.	up to 35 W	up to 20 min	up to 100 W	15 – 70 min
	Sunday			
	Summer		Winter	
	Magnitude	Duration	Magnitude	Duration
9:00 a.m. – 3:00 p.m.	up to 100 W	30 – 90 min	up to 20 W	15 – 90 min
6:00 p.m. – 10:30 p.m.	up to 75 W	15 – 70 min	up to 100 W	15 – 60 min

the sun, cloud coverage, ambient temperature, irradiation, humidity, just to name a few. Therefore, PV is expected to add significant variability to the load shape and should be considered in the design of control methods.

The performance of the PV and the variability depends also on the region, season, time of day and size of the plant. Around noon, the capacity factor can vary between 20 % and 60 % in summer and 10 % and 30 % in winter [91]. Variable cloud coverage can cause up to 60 % variation of capacity in the range of a few seconds for small PV, up to minutes for PV plants with MW capacity [92]. Sunrise and sunset cause variations of ca. 10 % over a period of 15 minutes.

Previous studies show that 99 % of all PV variations last less than 20 minutes. Therefore, PV variations are relevant for the short-term compensation and have to be taken into consideration.

For the study of deviations, detailed data from the generation profile of a PV installation of 100 kW in Gleisdorf, Austria, were friendly provided by the authors of [18]. The data contains the PV output on a variably cloudy day with extreme variations. For this study, the variations were analyzed compared to the expected generation for a cloudy day with continuous cloud coverage and lower irradiance. The variable cloud coverage caused four major deviations of 15 – 45 % in the range between 10 and 25 minutes and one of 45 % and 40 minutes. Furthermore, over 30 variations of 10 – 30 % of 5 – 7 minutes and numerous variations lower than 5 % and 5 minutes were detected (see 5.8).

Due to the limited amount of data and the observed extreme case which seems to occur very rarely according to [93], the presented results can be used solely as a basis for general conclusions. How-

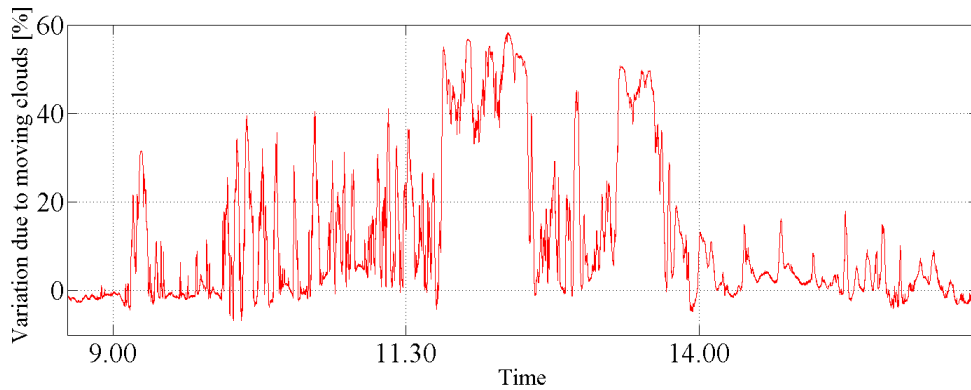


Figure 5.8: Variations of the PV output on a variably cloudy day (13.09.2004, Gleisdorf, Austria)

ever, they confirm the statements introduced above and set an upper limit for the expected PV variability, which the short-term balancing should account for.

5.3.5 Assignment of Dispatchable Resources

To conclude the deviation study and to provide a basis for the motivation of the short-term compensation algorithm, here the deviation categories are linked to dispatch resources, often considered for Smart Grid strategies. Beside the heating systems which are primarily relevant for 2DSM, also domestic appliances are grouped and listed based on [94] and [95].

For different HP technologies and the operation conditions, their consumption varies in a wide range between 2 and 10kW. Start-up time to full power is up to one minute. Due to issues with efficiency and lifetime of the devices, HP can be switched up to 3 – 4 times per hour. CHPs are available in different configurations according to the necessary thermal power and the available storage. nCHP perform in the range under 2.5kW_e and 7.5kW_{th}, and μCHP under 5kW_e and 5kW_e and 3 – 15kW_{th}. Both are typically installed in single or double dwellings and small businesses. Start-up times are in the range of 5 – 10 minutes. μCHPs are blocked for 30 minutes after switching for combustion engine technologies and for 45 minutes for fuel cells. Therefore, they can be switched up to 2 times per hour.

[94] and [95] provide a detailed characterization of the peak load, the common demand pattern, the frequency of use and the synergistic potential of dispatchable household appliances to be linked to sustainable energy sources. According to the sources, the power demand of washing machines, dish washers and tumble dryers is in the range of 0 – 2kW with operation time 1.5 – 2 hours. Power Demand of oven and stove is 0.6 – 1.5kW. Air conditioners and electric storage heaters operate in the range of 4 – 5kW.

Table 5.3 contains the assignment of dispatchable energy resources to the defined deviation categories. The category allocation considers the average power dispatch and the operation time of

Table 5.3: Definition of deviation categories and assignment of appliances

Power Dispatch		Duration		
		< 20 minutes	< 45 minutes	< 2h
	< 2 kW	—	Freezer, Oven, Stove	Washing machine Tumble Dryer Dish washer
	2 – 5 kW	nCHP		
		Air conditioning Electrical storage heater	—	—
	> 5 kW	HP, μ CHP		

the devices. The operation time of heating systems varies according to the storage capacity.

This study is used as a first step for the definition of the requirements for the short-term compensation algorithm. During runtime, the deviation analysis is a preliminary step for the compensation algorithm presented in section 5.5.

Based on the introduced underlying principles for load forecasting and categorization of schedule deviations, next two sections comprise the description of the two phases of the implemented energy management algorithm for city districts. The next section presents a centralized and a decentralized approaches for the scheduling of heating systems and an investigation of the results of an implemented test scenario.

5.4 Scheduling of Electro-Thermal Heating Systems in a City-District Energy System

The first phase of the coordination strategy within 2DSM comprise a day-ahead scheduling. The steering signal adopted is a dynamic pricing signal which reflects indirectly the availability of renewable energy sources. Consequently, the coordination aims to increase the integration of RES.

In this section a multi-agent based strategy with a centralized and a decentralized coordination approach are investigated. The centralized coordination scheme realizes a demand side management concept in which the DERs are scheduled collectively to achieve a common goal, while meeting the individual electrical and thermal demand. It should be noted that such a centralized coordination has limited scalability. *However, the scalability can be achieved through inter-coordination between the different subsystems.*

In the decentralized approach, the schedules of the DERs are not directly determined but induced through dynamic and variable electricity pricing. Hence, the latter approach is defined as a demand response strategy.

The structure of both concepts is kept general with *no mapping onto actual stakeholders*. Further, no assumption on the ownership of the functions are made, as different countries may have different commercial agreements. Moreover, the interaction with other entities e.g. Distribution System Operator (DSO) to check the feasibility of the optimal scheduling is foreseen but not implemented.

Centralized Approach

The MAS for DSM is depicted in Figure 5.9 and comprises 6 agents with specific functionalities: aggregator, house, renewable, trader, market and weather. The weather agent performs or queries a forecast of the outdoor air temperature, solar irradiation, and wind speed and forwards this information to the building and renewable agents. A house agent uses the outdoor temperature prognosis as well as recorded heat demand and outdoor temperature of the past periods to forecast the heat demand for the next day and forwards this result to the aggregator agent. The thermal demand forecast is carried out using 5.2.2. The house agents send their device characteristics e.g. modulation level, nominal power and efficiency to the aggregator agent. Along with the heat demand forecasts, these characteristics are used as input parameters and restrictions for the schedules' optimization. The renewable agent uses the wind speed and solar irradiation forecasts to determine the available solar and wind energy and forwards this information to the aggregator. The market agent determines the price of electricity import and export.

In the DSM scheme, the aggregator acts as the main coordinator of the DERs. The functions of the aggregator comprise electrical demand forecast (of appliances and lights exclusively), schedule optimization and the aggregation of total electrical balance. The schedule determination is based on Mixed Integer Programming (MIP) model which is introduced in the next section. The electrical demand forecast is carried out for all the buildings collectively, thus reducing the forecast error. The prediction algorithm is presented in section 5.2.1. The aggregated electrical balance in the grid connected model includes the electrical lack and surplus and is forwarded to the trader agent. The latter ensures that the surplus is exported and the lack is compensated from other micogrids or the macrogrid. In island mode, the trader has no role as the loads are matched by the internal DER solely. This is realized by adjusting the restrictions for the schedules' optimization.

Decentralized Approach

In the MAS structure for DR depicted in Figure 5.10 several agents maintain the same functions mainly the weather, renewable and trader agents. The aggregator agent is no more the main coordinator and its functions are reduced to aggregating the total electrical demand as well as lack and surplus. The functions of the house agents now include the individual electrical demand forecast and the schedule generation. The steering signal for the scheduling on building level is provided by the market agent as a dynamic price signal. The aggregator agent receives the electrical

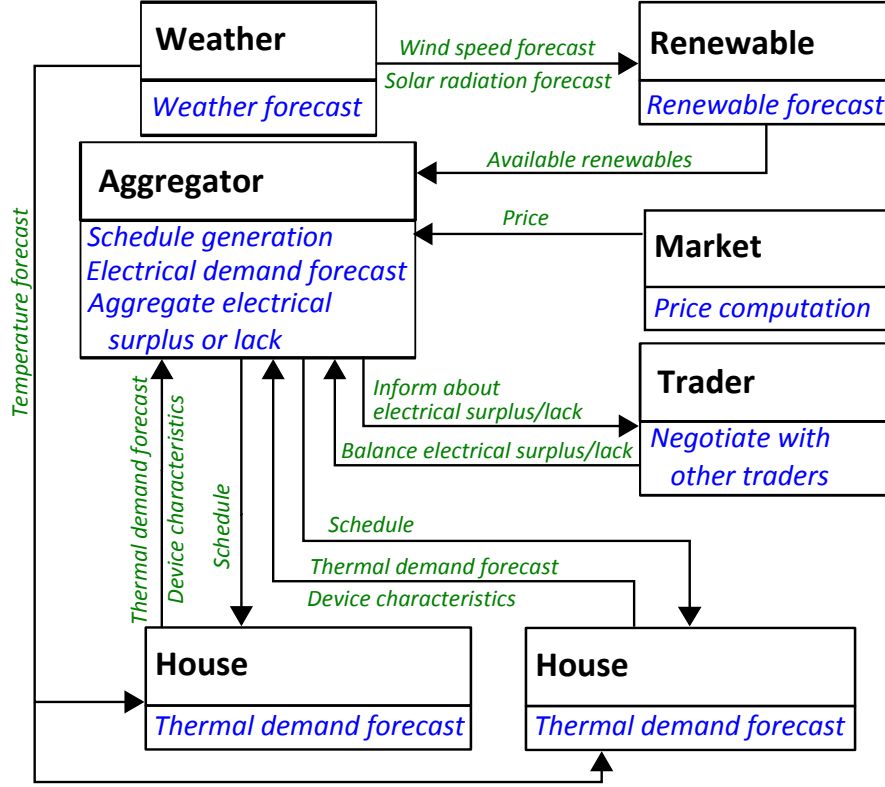


Figure 5.9: Flow chart of the central coordination scheme [96]

demand forecast and schedules of the DERs from the buildings and offsets these against the available renewables. The residual demand as well as the available renewable energy and the device characteristics are forwarded to the market agent, which computes the price signal.

The day-ahead schedules are determined on building level based on an iterative approach. The price signal is initiated by the market by comparing the sum of all electrical demand forecasts with the available renewables. The iteration begins by applying this price signal to the largest CHP. In the following steps, the price signal is updated according to a merit order scheme resulting from the on-off-state of each DER and the interaction with the macrogrid. These updated price signals are used to schedule HPs and CHPs alternatingly. If all restrictions are satisfied, each building has scheduled the corresponding heating devices at least once, and the price signal following two consecutive iterations remains unchanged, the process has reached convergence. The alternating scheduling of CHPs and HPs has proved to converge with the minimum number of iterations.

5.4.1 MIP Model

This section presents the mathematical modeling for the scheduling phase. The heating systems considered are bivalent DERs i.e. HPs or CHPs systems equipped with a peak boiler and a water

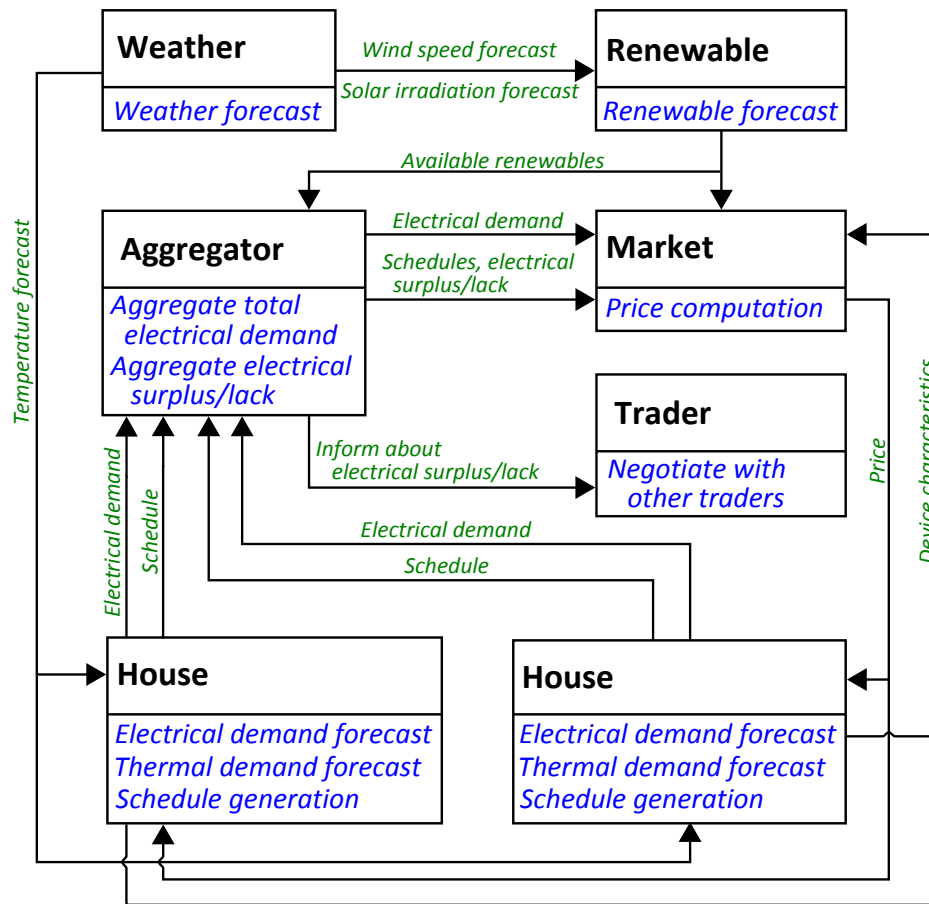


Figure 5.10: Flow chart of the decentral coordination scheme [96]

storage tank. A parallel operation mode is foreseen. The thermal storage unit allows for flexible operation of the heat generators and enables shifting the electrical consumption and production patterns.

The following subsection defines the general optimization problem formulation and the underlying technical constraints of the heat generators and finally their extension towards a collective scheduling formulation.

Optimization Problem

In our market based approach, the scheduling aims to provide the most economical operation of the DERs. Therefore, the optimization problem is formulated as a maximization of the profit p which is defined as the difference between costs c and revenues r . the costs considered represent the operating costs exclusively. The operation costs of storage are mainly maintenance and are therefore neglected. The goal to increase the integration of integration of renewable energies is

pursued by assigning them the cheapest energy price.

$$\mathbf{max} \quad p \quad (5.18)$$

$$\mathbf{subject\ to} \quad p = r - c \quad (5.19)$$

$$c = c_{\text{Storage}} + c_{\text{Boiler}} + c_{\text{DER}} \quad (5.20)$$

Storage Model

The mathematical model of the storage unit is based on the energy balance that is shown in figure 5.11. The generation heat flux comprises the aggregation of the DERs and the peak unit generation. The output heat flux is the building's heat demand as well as the storage heat losses. A

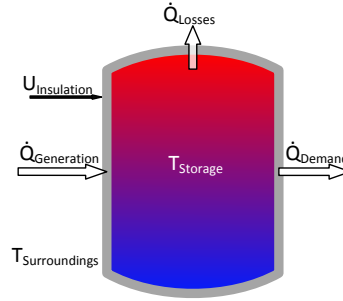


Figure 5.11: Simplified model of the storage unit

storage charge and discharge efficiency is introduced, because heat transfer always suffers from losses. An empirical value of 98 % is used according to [97]. Consequently, the rate of change of the storage's inner energy can be formulated as:

$$\frac{d}{dt} (U_{\text{Storage}}(t)) = \dot{Q}_{\text{Generation}}(t) \cdot \eta_{\text{charge}} - \frac{\dot{Q}_{\text{Demand}}(t)}{\eta_{\text{discharge}}} - \dot{Q}_{\text{Losses}}(t) \quad (5.21)$$

t is the time step which is set to 15 minutes. The storage's losses to the surroundings are assumed to be predominantly due to heat conduction and are expressed as:

$$\dot{Q}_{\text{Losses}}(t) = A_{\text{Storage}} \cdot L_{\text{Insulation}} \cdot [T_{\text{Storage}}(t) - T_{\text{Surroundings}}] \quad (5.22)$$

In equation 5.22, A_{Storage} describes the surface area of the storage, $U_{\text{Insulation}}$ stands for the storage's insulation coefficient, T_{Storage} is the mean temperature inside the storage unit and $T_{\text{Surroundings}}$ the temperature of the immediate surrounding atmosphere of the storage, which is considered to be constant. The inner energy is expressed in terms of its average temperature:

$$\frac{d}{dt} (U_{\text{Storage}}(t)) = V_{\text{Storage}} \cdot \rho_{\text{Water}} \cdot c_{\text{Water}} \cdot \frac{d}{dt} (T_{\text{Storage}}(t)) \quad (5.23)$$

In this equation, V_{Storage} denotes the volume of the storage unit, ρ_{Water} the density of water and c_{Water} the heat capacity, each at 1 bar pressure level and 45 °C. The differentiation operator can be discretized with the first-order backwards difference expression. The time resolution of fifteen minutes is considered by dividing by $15 \cdot 60 = 900$. Through inserting 5.23 in 5.21, the following equations to describe the storage unit's current load are obtained:

$$T_t^{\text{Storage}} - T_{t-1}^{\text{Storage}} = \frac{\dot{Q}_t^{\text{Generation}} \cdot \eta_{\text{charge}} - \frac{\dot{Q}_t^{\text{Demand}}}{\eta_{\text{discharge}}} - \dot{Q}_t^{\text{Losses}}}{V_{\text{Storage}} \cdot \rho_{\text{Water}} \cdot c_{\text{Water}}} \cdot 900 \quad \forall t \geq 2 \quad (5.24)$$

$$(5.25)$$

T_t^{Storage} is restricted, so that the following bounds result for all times t :

$$T_{\text{Storage,min}} \leq T_t^{\text{Storage}} \leq T_{\text{Storage,max}} \quad (5.26)$$

Further restrictions involve the charge and discharge rate of the storage unit. Like done in [97], both restrictions limit the charge and discharge rate to 25 % of the entire storage capacity, so that the storage can be fully loaded or unloaded within one hour. The corresponding equations are:

$$T_t^{\text{Storage}} - T_{h-1}^{\text{Storage}} \leq T_{\text{Charge,max}} \quad \forall t \geq 2 \quad (5.27)$$

$$T_{t-1}^{\text{Storage}} - T_h^{\text{Storage}} \leq T_{\text{Discharge,max}} \quad \forall t \geq 2 \quad (5.28)$$

For the first time step, these equations are modified by exchanging T_{t-1}^{Storage} with the temperature of the previous scheduling, $T_{\text{Storage,init}}$. The following table displays an overview of all constant parameters and their corresponding values that are used in the storage model:

Table 5.4: Constant parameters in the storage model

Variable	Physical unit	Value
c_{Water}	J/(kg K)	4180
ρ_{Water}	kg/m ³	975
$T_{\text{Surroundings}}$	°C	20
$T_{\text{Storage,min}}$	°C	20
$T_{\text{Storage,max}}$	°C	65

Modeling of Heat Generators

The aggregated generation of the bivalent heating system is the sum of the boiler's and the DER's heat generations:

$$\dot{Q}_t^{\text{Generation}} = \dot{Q}_t^{\text{DER}} + \dot{Q}_t^{\text{Boiler}} \quad (5.29)$$

The boiler is assumed to modulate between the switching on threshold ($\dot{Q}_{\text{minimal}}^{\text{Boiler}}$) and the nominal heat output ($\dot{Q}_{\text{nominal}}^{\text{Boiler}}$):

$$b_t \cdot \dot{Q}_{\text{minimal}}^{\text{Boiler}} \leq \dot{Q}_t^{\text{Boiler}} \leq b_t \cdot \dot{Q}_{\text{nominal}}^{\text{Boiler}} \quad (5.30)$$

The binary variable b_t equals 1 if the boiler is turned on at time step t and 0 otherwise. If the boiler is shut down, $\dot{Q}_t^{\text{Boiler}}$ is forced to be 0, if it is active, $\dot{Q}_t^{\text{Boiler}}$ is between the minimal and nominal heat output. $\dot{Q}_{\text{minimal}}^{\text{Boiler}}$ is set equal to 10 % of $\dot{Q}_{\text{nominal}}^{\text{Boiler}}$.

The operational costs of the boiler can be computed with the following equation, where c_{gas} denotes the natural gas price and η_{Boiler} the efficiency of the boiler:

$$c_{\text{Boiler}} = \sum_{t=1}^{t_{\text{max}}} c_{\text{gas}} \cdot \frac{\dot{Q}_t^{\text{Boiler}}}{\eta_{\text{Boiler}}} \cdot 900 \quad (5.31)$$

Next, the equations that HPs and CHPs have in common are formulated, while the specific equations are presented in the subsequent subsections. The generated heat by either the CHP or HP, assuming a non modulated operation, can be computed as:

$$\dot{Q}_t^{\text{DER}} = x_t \cdot \dot{Q}_{t,i} \quad (5.32)$$

The variable x_t is restricted by $0 \leq x_t \leq 1$. If x_t is zero, the heat generator is turned off, otherwise it is active. The heat output $\dot{Q}_{t,i}$ is constant for CHP units. For heat pumps, $\dot{Q}_{t,i}$ is time dependent, since the COP is a function of the temperature. The heat pump's heat output is computed using the corresponding data sheet based on a linearization approach in function of the outdoor air temperature.

Heat Pump Model

A heat pump does not generate any revenues, the r variable in equation 5.19 is set to zero:

The costs caused by the heat pump can be separated into the consumed electricity and the costs accounting for state transitions, namely shutdown and startup costs. For reasons of simplicity, the transitions costs are set to zero.

$$c_{\text{HP}} = c_{\text{el}} + c_{\text{Transitions}} \quad (5.33)$$

The electrical consumption can be calculated by coupling the produced heat flow rate with the COP:

$$P_t^{el} = \frac{x_t}{COP_{t,i}} \cdot \dot{Q}_{t,i} \quad (5.34)$$

The resulting costs for electricity consumption is formulated with c_t^{el} stands for the as:

$$c_{el} = \sum_{t=1}^{t_{\max}} c_t^{el} \cdot P_t^{el} \cdot 900 \quad (5.35)$$

Combined Heat and Power Model

The electricity balance for a dwelling equipped with a CHP unit can be expressed as follows:

$$P_t^{el,CHP} + P_t^{Auxiliary} = P_t^{Surplus} + P_t^{Demand} \quad (5.36)$$

The building's electrical demand (P_t^{Demand}) comprises the electricity consumption of its electrical appliances, lighting and domestic hot water. This load can be met by the CHP or though additionally bought electricity ($P_t^{Auxiliary}$). In case the generated electricity ($P_t^{el,CHP}$) exceeds the demand, the surplus electricity can be sold and inducted to the electrical grid ($P_t^{Surplus}$). Since it is not possible to buy and sell electricity at the same time, it is necessary to introduce the following restriction:

$$\min \{P_t^{Auxiliary}; P_t^{Surplus}\} = 0 \quad (5.37)$$

Equation 5.37 is non-linear, therefore additional variables and restrictions are used. Upper boundaries for $P_t^{Auxiliary}$ and $P_t^{Surplus}$ are given with $M^{Auxiliary}$ and $M^{Surplus}$. The value of $M^{Auxiliary}$ equals the maximum of the electrical demand in the current optimization period. The upper boundary of $P_t^{Surplus}$ is the CHP unit's nominal electrical output. The binary variable d_t is necessary to prevent the simultaneous purchase and disposition of electricity. If auxiliary electricity is purchased, d_t is set to 1 and if surplus electricity is sold to the grid, d_t is 0.

$$0 \geq P_t^{Auxiliary} - M^{Auxiliary} \cdot d_t \quad (5.38)$$

$$0 \geq P_t^{Surplus} - M^{Surplus} \cdot (1 - d_t) \quad (5.39)$$

The revenue resulting from the use of the CHP is the sum of the earnings from the sold electricity amount and the governmental subsidies for CHP units. The entire produced electricity is subsidized with p_{el}^{sub} . The inducted electricity is sold at $p_{Inducted}$.

$$r = \sum_{t=1}^{t_{\max}} \left(p_{\text{el}}^{\text{sub}} \cdot P_t^{\text{el,CHP}} + p_{\text{Inducted}} \cdot P_t^{\text{Surplus}} \right) \cdot 900 \quad (5.40)$$

The generated electricity at time t is calculated with:

$$P_t^{\text{el,CHP}} = x_t \cdot \dot{Q}_i \cdot \sigma \quad (5.41)$$

Operational costs of the CHP unit can be separated into costs for fuel, state transitions and also for purchasing additional electricity ($c_{\text{interaction}}$):

$$c_{\text{CHP}} = c_{\text{fuel}} + c_{\text{transitions}} + c_{\text{interaction}} \quad (5.42)$$

Fuel costs can be calculated as:

$$c_{\text{fuel}} = c_{\text{gas}} \cdot \sum_{h=1}^{h_{\max}} \left[x_t \cdot \dot{Q}_i \cdot \frac{\sigma_i}{\eta_i} \right] \cdot 900 \quad (5.43)$$

The costs arising from state transitions are neglected, the costs for additionally required electricity are calculated as follows:

$$c_{\text{interaction}} = \sum_{t=1}^{t_{\max}} c_t^{\text{el}} \cdot P_t^{\text{Auxiliary}} \cdot 900 \quad (5.44)$$

Cluster Scheduling

On a cluster level, the above presented models are used individually for the decentralized scheduling. In the centralized scheduling or DSM concept, further formulations are introduced to emulate the common electrical grid.

In DSM, the participants are presumed to cooperate towards a common goal. Therefore, the optimization problem can be further expressed as maximize the total profit that comprises costs for additional electricity and gas, as well as revenue generated from selling electrical surplus and governmental subsidies.

$$\max \quad r^{\text{total}} = r^{\text{total}} - c^{\text{total}} \quad (5.45)$$

$$\text{subject to} \quad r^{\text{total}} = r^{\text{CHP}} + r^{\text{interaction}} \quad (5.46)$$

$$c^{\text{total}} = c^{\text{HP}} + c^{\text{CHP}} + c^{\text{interaction}} \quad (5.47)$$

The revenue generated by CHP units, as defined in equation 5.40, has to be adjusted, because surplus is now not the surplus of a single household, but of the entire cluster of buildings. Thus, the revenue of CHP units is equal to the generated subsidies:

$$r^{\text{CHP}} = p_{\text{el}}^{\text{sub}} \cdot \sum_{s=1}^{s_{\text{CHP}}} \sum_{t=1}^{t_{\text{max}}} P_{t,s}^{\text{el,CHP}} \cdot 900 \quad (5.48)$$

In equation 5.48, the total number of CHP units in the cluster is given with s_{CHP} . The total amount of heat pumps is s_{HP} .

The heat pump's costs also have to be adjusted, because costs for additionally required electricity are computed for the entire cluster of buildings and not for individual households. Therefore, the heat pump equipped buildings' costs equal the gas consumption of their boiler:

$$c_{\text{HP}} = c_{\text{gas}} \cdot \sum_{s=1}^{s_{\text{HP}}} \sum_{t=1}^{t_{\text{max}}} \frac{\dot{Q}_{t,s}^{\text{Boiler}}}{\eta_{\text{Boiler},s}} \cdot 900 \quad (5.49)$$

The costs of the CHP equipped buildings are the entire gas consumption of the CHP unit and the boiler:

$$c_{\text{CHP}} = c_{\text{gas}} \cdot \sum_{s=1}^{s_{\text{CHP}}} \sum_{t=1}^{t_{\text{max}}} \left[\frac{\dot{Q}_{t,s}^{\text{Boiler}}}{\eta_{\text{Boiler},s}} + \frac{x_{t,s} \cdot \dot{Q}_s \cdot \sigma_s}{\eta_s} \right] \cdot 900 \quad (5.50)$$

Interaction costs only result from externally bought electricity:

$$c_{\text{interaction}} = \sum_{t=1}^{t_{\text{max}}} c_t^{\text{el}} \cdot P_t^{\text{Auxiliary}} \cdot 900 \quad (5.51)$$

The revenue from selling electricity equals:

$$r^{\text{interaction}} = p_{\text{Inducted}} \cdot \sum_{t=1}^{t_{\text{max}}} P_t^{\text{Surplus}} \cdot 900 \quad (5.52)$$

The electrical side can be balanced as follows, to compute the amount of necessary additional electricity, resp. electrical surplus at each time step t :

$$P_t^{\text{Renewables}} + \sum_{s=1}^{s_{\text{CHP}}} P_{t,s}^{\text{el,CHP}} + P_t^{\text{Auxiliary}} = P_t^{\text{Surplus}} + P_t^{\text{Demand}} + \sum_{s=1}^{s_{\text{HP}}} P_{t,s}^{\text{el,HP}} \quad \forall t \quad (5.53)$$

In equation 5.53, $P_t^{\text{Renewables}}$ stands for the available renewables at time step t . The computation of $P_t^{\text{Renewables}}$ is explained in section 5.4.2. The entire electrical demand of electrical appliances is P_t^{Demand} . Surplus and additional electricity cannot be unequal to zero at the same time step, therefore equations 5.38 and 5.39 are also used in the grid connected models.

A reference scenario is given in scheduling the heating devices in a heat driven mode. For this case, the objective function is changed. In the heat-driven scheduling, the generated amount of heat is minimized, therefore the objective function becomes:

$$\text{Minimize} \quad \sum_{t=1}^{t_{\max}} \left[\sum_{i=1}^{s_{\text{CHP}}} \dot{Q}_{t,i}^{\text{Generation}} + \sum_{j=1}^{s_{\text{HP}}} \dot{Q}_{t,j}^{\text{Generation}} \right] \cdot 900 \quad (5.54)$$

The starting order also has to be set in the heat-driven scheduling. The boiler can only be turned on to support the main heating device (CHP or heat pump unit), if the heat output of the main heating device is not sufficient to fulfill the current demand. This restriction is given with:

$$b_{t,s} \geq v_{t,s,n} \quad \forall t, \forall s = 1 \dots s_{\text{CHP}} \quad (5.55)$$

$$b_{t,s} \geq v_{t,s,n} \quad \forall t, \forall s = 1 \dots s_{\text{HP}} \quad (5.56)$$

5.4.2 Investigation and Results

The performance of the aforementioned market based scheduling concepts is investigated by applying these to a test case comprising 34 buildings from the Lucas Cranach street. The scenario set up is first presented followed by the evaluation of the results.

Scenario Definition

The buildings are equipped individually with a bivalent air-water HP or CHP system. The distribution of the units is carried out systematically by choosing the desired power ratio of CHPs to HPs. In this case, a ratio of 110 % is adopted empirically. This ratio is specifically chosen to enable a possible autonomous operation of the cluster. Accordingly, a systematic distribution of DERs is done by assigning HPs to the buildings with the lowest nominal heating load and CHPs to the one with the highest. This ensures the practicability of this setup, since CHPs are economically feasible in dwelling with large heating demand which allows for a long operation of these units. As a result HPs are installed in 17 buildings and the remaining 17 dwelling are equipped with CHPs. It should be noted that the resulting identical number of buildings is a mere coincidence.

The dimensioning of the heating systems is done according to the standard technical conventions assuming a parallel operation mode. For HPs, a bivalence point of 5 °C is used to determine the HPs powers and the corresponding peak unit as depicted in Figure 5.12. Further optimization strategies for the design of energy conversion units are investigated in [98].

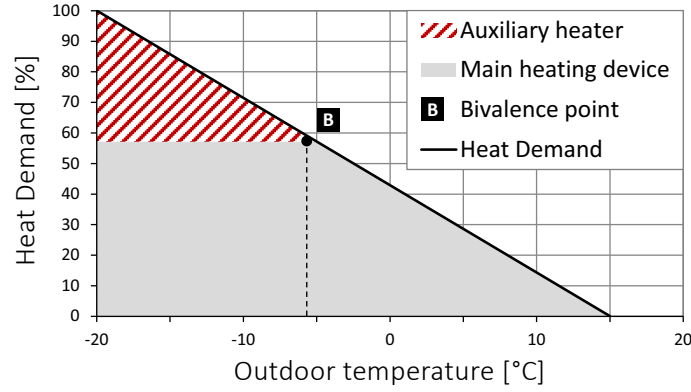


Figure 5.12: Bivalent design of a heat pump system in parallel operation

While heat pumps are dimensioned based on the ambient temperature, the size of a CHP unit is derived from the load duration curve displayed in Figure 5.13. Typical annual full load hours which should exceed 4000h/a are desired to provide an economic viability. This lower limit has been adopted to provide the desired load flexibility within the cluster. One common storage capacity of 1000l is installed in all 34 buildings.

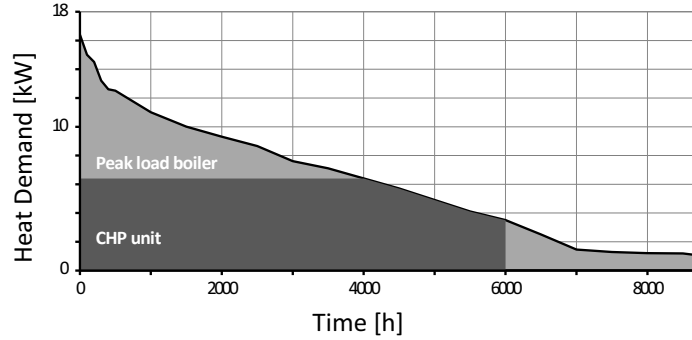


Figure 5.13: Exemplary load duration curve of a a CHP

The renewable energy availability is estimated using the solar global radiation and wind speed profile from the weather data used for the building simulations introduced in chapter 4. The PV generation is calculated using the Equation 5.57

$$P_t^{\text{solar}} = I_t^{\text{direct}} \cdot A^{\text{solar}} \cdot \eta^{\text{solar}} \quad (5.57)$$

The wind energy is mainly a function of the wind speed w_t [99]. The amount of electricity that can be generated from an airflow through a wind energy converter (P_t^{wind}) is limited with:

$$P_t^{\text{wind}} = 0,5 \cdot w_t^3 \cdot A^{\text{wind}} \cdot \rho^{\text{air}} \cdot C^{\text{Betz}} \quad (5.58)$$

In equation 5.58, A^{wind} denotes the area that is spanned by the rotor blades, ρ^{air} is the density of air and the factor C^{Betz} stands for the Betz coefficient (~ 0.59). Wind turbines have a cut-in speed ($w^{\text{cut-in}}$), below which the air flow's torque is insufficient to rotate the blades, a rated output wind speed ($w^{\text{rated speed}}$) above which the output power is limited to prevent mechanical damages from exceeding a rotational speed limit and a cut-out speed ($w^{\text{cut-out}}$) above which the turbine is turned off. Therefore, the available wind energy is computed according to the current wind speed. If it is below the cut-in or above the cut-out velocity, the available electricity from wind is set to zero. If the current wind speed is between the rated output wind speed and the cut-out, the current wind output is set to the rated output power (P^{peak}). If the current wind speed is between the cut-in and the rated output wind speed, the available wind speed is computed with a cubic function that satisfies the following constraints:

- $f(w^{\text{cut-in}} + 0, 5) = 0$
- $\lim_{\delta \rightarrow 0} f(w^{\text{cut-in}} + 0, 5 - \delta) = 0$
- $f(w^{\text{rated speed}}) = P^{\text{peak}}$
- $\lim_{\delta \rightarrow 0} f(w^{\text{rated speed}} + \delta) = P^{\text{peak}}$

Figure 5.14 depicts the results of this modeling approach. Further, Table 5.5 provides an overview of the different parameters and assumptions used to generate the renewable energy generation profile. The number of wind turbines available is estimated at 5, each with rotor diameter of 12 m.

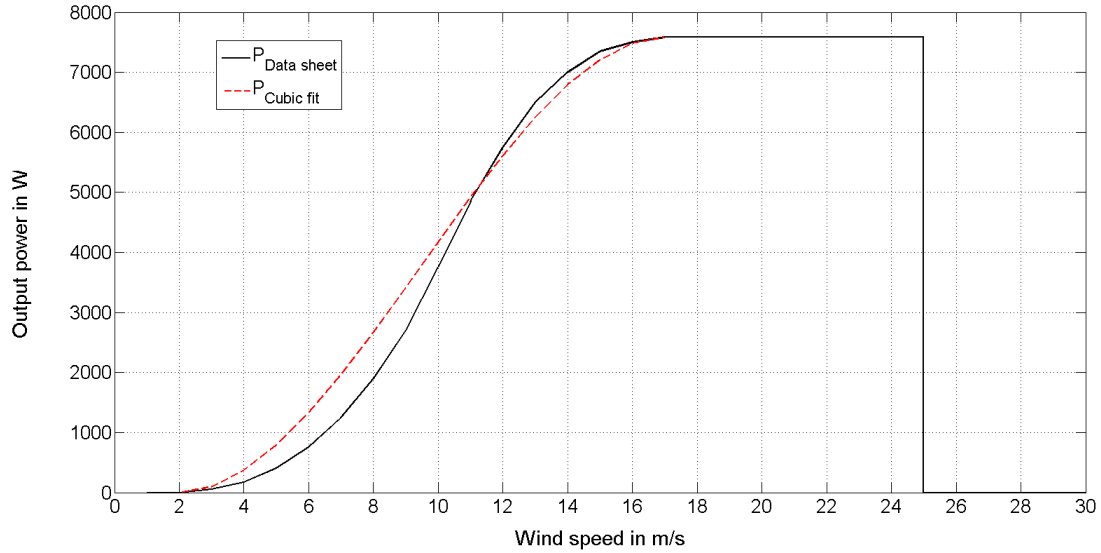


Figure 5.14: Wind energy performance chart

Table 5.5: Parameters for the renewable energy generation

Data	Physical unit	Value
A_{solar}	m^2	680
η_{solar}	—	0.22
$w_{\text{cut-in}}$	$\frac{\text{m}}{\text{s}}$	2
$w_{\text{cut-out}}$	$\frac{\text{m}}{\text{s}}$	25
w_{nominal}	$\frac{\text{m}}{\text{s}}$	11
d_{rotor}	m	12
$n_{\text{wind turbines}}$	—	5

Results

In this section, the coordination of the distributed energy conversion units as well as the integration of the available renewable energy within the different scheduling schemes is evaluated.

Figures 5.15, 5.16 and 5.17 shows the electrical balances on the grid side. The residual demand represents the difference between the electricity demand ('D') and the available renewable energy generation ('R'). If this line is below zero, the renewable supply is larger than the demand.

The grid interaction is illustrated by the difference of the additionally bought electricity ('B') and the surplus ('S') which the excess energy of renewables or locally generated electricity from the CHP units. A negative value indicates a surplus which is exported to the macrogrid.

The heat driven results are depicted in Figure 5.15. The grid balance displays large peaks of imports and export which is a clear indication of the lack in coordination as HPs and CHPs are operated in this scenario to meet the energy demand without any consideration of the availability of renewable energy or the peaks of electrical demands.

The results of the centralized coordination are displayed in Figure 5.16. This strategy minimizes the imports and exports significantly. Additional energy is mainly bought when the demand greatly outweighs the renewable generation or during the summer period in which the CHPs cannot be operated to compensate the electrical demand due to the lack of heat demand. When renewables outweigh the demand, the scheduling attempts to shutdown the CHPs and consequently avoid producing large surpluses. Simultaneously, the heat pumps are activated to take advantage of the availability of renewable energy. In times of high demand, the scheduling minimizes the additionally required amount of electricity by deactivating the HPs and activating the CHP units.

The results of the decentralized scheduling are shown in Figure 5.17. Compared to the centralized scheduling, the run time of CHPs is significantly increased. Figure 5.18 displays the average load hours for the CHPs units as well as the peak boilers for all three scenarios. In the heat-driven configuration the average load hours are around 2700. In this scenario, the CHPs operation is limited to meeting the thermal demand which results in low operating hours. The latter increase

to 4200 and 5400 hours in the centralized and decentralized schemes, respectively, which is a clear indication to an electrical driven operation. In both strategies, the CHPs are used to compensate the lack of renewable energies and therefore achieve a higher usage rate.

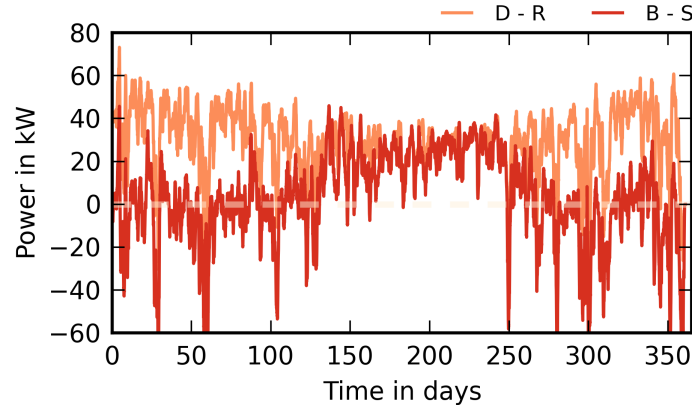


Figure 5.15: Exemplary results of the heat driven operation

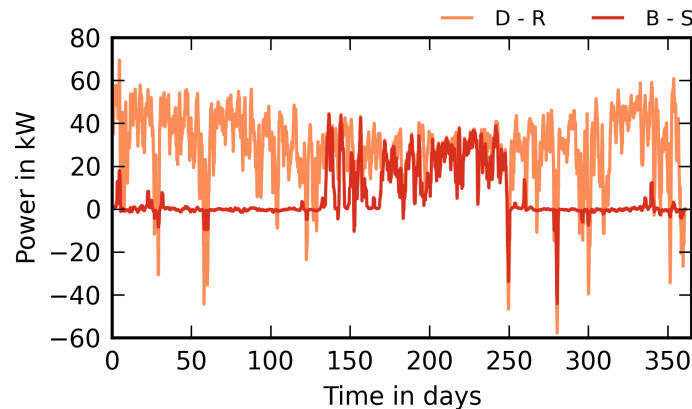


Figure 5.16: Exemplary results of the centralized scheduling

In the decentralized strategy, the individual goal to maximize the profit is relatively dominant and leads to very high run times of the CHPs. Consequently, the total amount of surplus is drastically increased as shown in Figure 5.17. This can be drawn back to the fact that the CHP units are not able to anticipate the renewable energy generation. Instead, they only take into consideration the buildings' electrical demand for appliances, which is always present. Therefore, the CHP units are operated although the renewables already provide enough electricity to cover the buildings' primary demand. Consequently, the cluster displays a virtual power plant behavior. This indicates that the iterative approach for dynamic prices is unsuitable for achieving a balanced coordination and operation within the cluster compared to the centralized scheme.

The afore presented figures provide an overview on the behavior of the DERs and the grid status under the different scenarios setups. However, they don't deliver a clear evaluation of the coordi-

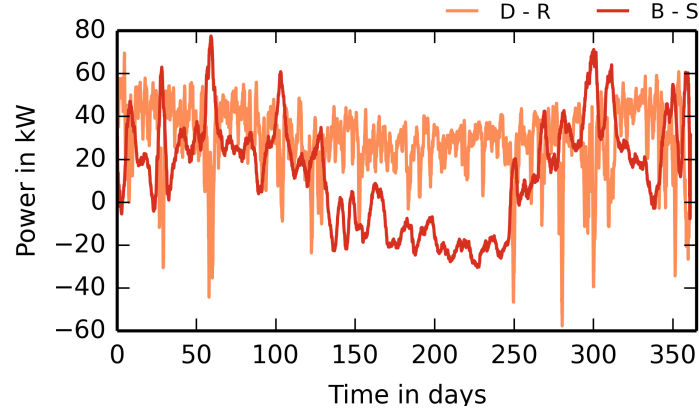


Figure 5.17: Exemplary results of the decentralized scheduling

nation of HPs and CHPs as well as the integration of renewable energies and the handling of excess generated electricity. Therefore, the indicator K is introduced in the equation 5.59 to quantify the degree of coordination. K is defined as the amount of electricity consumed by heat pumps times the additionally purchased electricity.

$$K = \sum_{t=1}^{t_{\max}} \sum_{s=1}^{S_{\text{HP}}} P_{t,s}^{\text{el,HP}} \cdot P_t^{\text{Auxiliary}} \quad (5.59)$$

The amount of additionally required electricity can be computed with equation 5.53 on page 86. The influences on $P_t^{\text{Auxiliary}}$ can be illustrated by rewriting this equation:

$$P_t^{\text{Auxiliary}} = \max \left\{ P_t^{\text{Demand}} + \sum_{s=1}^{S_{\text{HP}}} P_{t,s}^{\text{el,HP}} - \sum_{s=1}^{S_{\text{CHP}}} P_{t,s}^{\text{el,CHP}} - P_t^{\text{Renewables}}; 0 \right\} \quad (5.60)$$

$P_t^{\text{Auxiliary}}$ is large if the heat pumps are started during high demands and if the CHP units are turned off or renewables are barely available.

A low value for K indicates a high degree of coordination that is achieved by turning on heat pumps when $P_t^{\text{Auxiliary}}$ is small. The resulting values for K in the grid connected mode are listed in table 5.6. As the above analysis suggests, the centralized strategy has the best degree of coordination. Table 5.6 shows that the centralized scheme barely requires additional electricity from the macrogrid, thus K reaches a minimum. The decentralized scheme has a 80 % better coordination, compared with the heat-driven strategy.

Table 5.6: Degree of coordination

Unit	heat driven	centralized	decentralized
TW ²	14.65	0.74	2.72

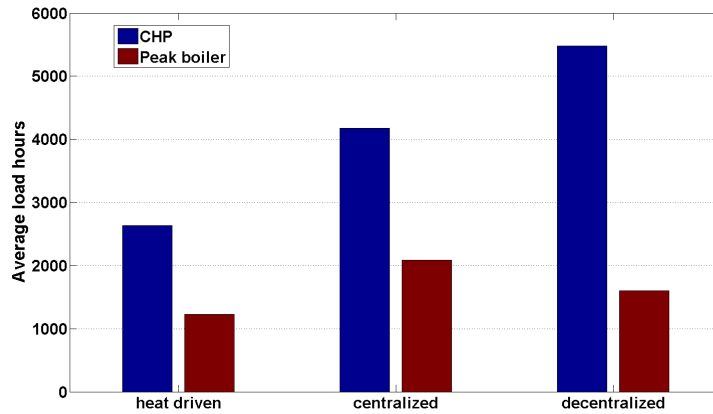


Figure 5.18: Average running hours of CHPs and peak boiler

Figure 5.20 depicts the coordination results and the load shifting events of the central energy management strategy. This figure illustrates one winter day in January during which considerable renewable generation is available. The upper subplot depicts the grid status. The lower subplot presents the active HPs and CHPs units respectively. The heat driven scenario for the same day is illustrated in Figure 5.19. The latter shows how additional energy is generated from CHPs between 13:00 and 14:00 as well as 16:00 and 17:00 o'clock despite the large availability of renewable energies. HPs are turned on at periods of high electrical demand between 8:00 and 10:00 o'clock resulting in further imports of electricity. Moreover, CHPs are turned on between 10:00 and 11:00 o'clock despite the large availability of renewable energies.

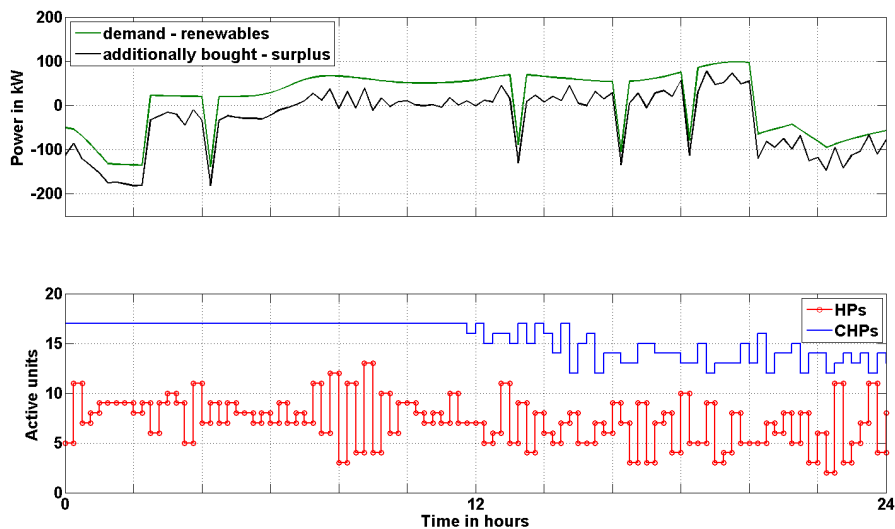


Figure 5.19: Heat driven operation results

The centralized energy management strategy in 5.20 shifts the operation of HPs into the slots in which large generation of renewables takes place and simultaneously turns off the CHPs e.g. between 4:00 and 5:00 as well as 13:00 and 14:00 o'clock. Furthermore, CHPs units are activated during the periods of large demand while simultaneously HPs are turned. As a result, a relative autarchic, i.e. energy independent, status is achieved. No additional electricity is imported from the external macrogrid. Moreover, the export is only restricted to the early phase in which a significant amount of renewables are available.

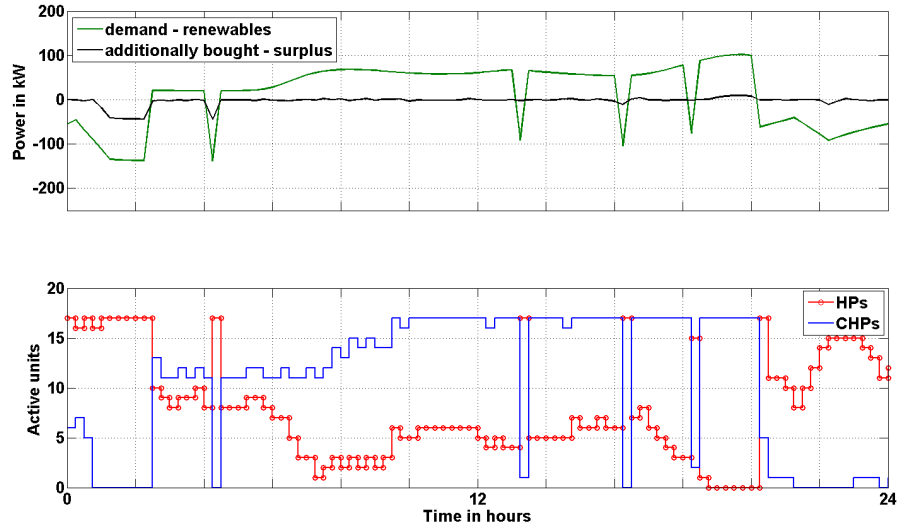


Figure 5.20: Centralized coordination results

As a final step in the energy management algorithm, the compliance of the schedules is monitored in the second phase of the introduced energy-management algorithm, the short-term compensation phase. It is presented in the following with the basic principle and with a case study illustrating its performance.

5.5 Short-Term Compensation of Deviations

This section describes the short-term phase of the energy management algorithm presented in section 5.4. In the first step of the short-term phase, the switching of the heating systems is coordinated in order to avoid transient effects due to simultaneous switching. Occurring deviations from the day-ahead schedule are detected, evaluated and analyzed continuously, and an adequate combination of resources to dispatch is calculated in order to compensate the deviations. The method evaluates short-term weather forecasts and user behavior forecasts, statistical data and signals from neighborhood clusters and the upper grid level. This section is based on the method and the preliminary results published in [100].

Contrary to other works in this field, the presented approach includes local state estimation and considers also grid aspects. Furthermore, deviations from the schedule are analyzed individually by every household based on statistics on residents' behavior and forecasts and classified according to the expected duration. The short-term load compensation builds on the scheduling and is designed as a cooperative approach, which follows global goals beneficial for all participants rather than the individual goals of the particular household.

Subsection 5.5.1 introduces the overall short-term compensation approach, as well as assumptions and constraints for the application of the algorithm. Furthermore, it creates a link to the deviation analysis and a definition of the flexibilities. The short-term compensation algorithm is presented in detail with the order of control actions in subsections 5.5.2 and 5.5.3.

5.5.1 System Description and Approach

The solution is based on a cooperative approach, neglecting financial incentives. This approach, contrary to approaches focused on the optimization of the financial gain of the individual household, could be beneficial for all market participants. On the one hand, monthly expenses are reduced with increasing installed flexibility. On the other hand, grid stability is secured and the conditions for integration of renewable energy sources are improved. Additionally, network expansion can be avoided, which saves additional costs for the grid operator and, therefore, for the customers.

Short-Term Compensation of Deviations

The energy management approach considers solely heating systems as sources of flexibility, which arises from the possibility for shifted switching due to the installed thermal storage. As already described, the control strategy has two phases, illustrated in 5.21. The short-term phase of the algorithm is illustrated in the bottom part of 5.21. In the beginning of every hour, the switching order of the heating systems is managed in order to avoid transient effects due to simultaneous switching. Furthermore, the coordination phase stipulates the definition of the schedules for this hour in resolution of 15 minutes by every household. Within the compensation phase, deviations from the schedule are predicted or detected, and an adequate strategy for their compensation is schemed according to the magnitude and character of the deviations. Signals for occurring deviations are processed continuously. The compensation algorithm is triggered every minute to update the generation and consumption forecasts, and to find an adequate combination of dispatch resources to compensate the deviation as depicted in 5.21.

Deviations

The study on schedule deviations showed that the character of the deviations, magnitude and duration, depend strongly on the observed time interval [87]. Due to the stochastic nature of human

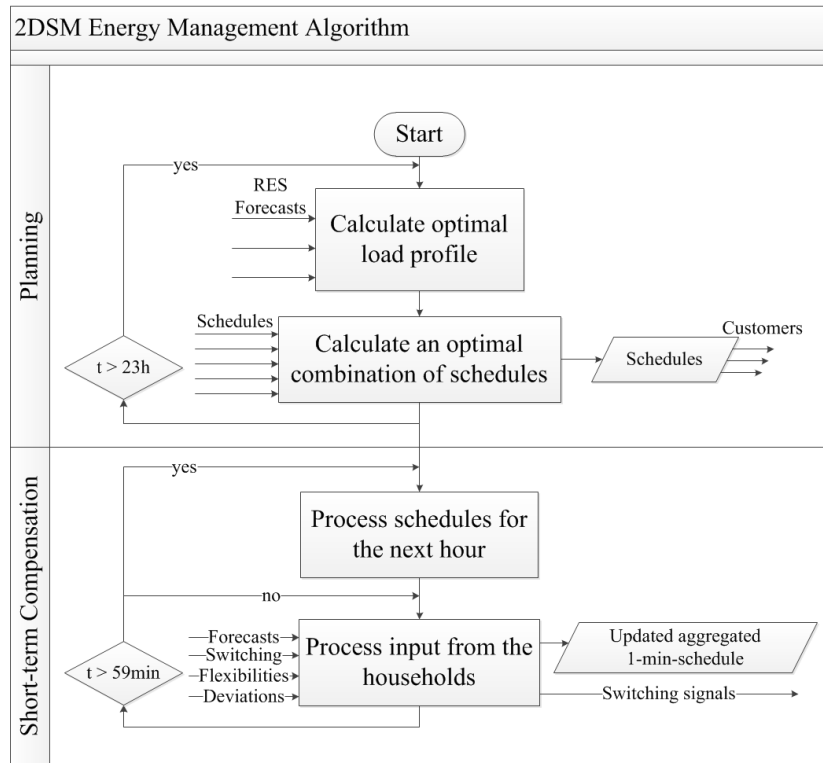


Figure 5.21: 2DSM Algorithm: Planning phase and short-term compensation phase

behavior, deviations, more numerous and with higher magnitude, are more likely when residents are present and active, this is mostly on mornings and evenings on weekdays and around noon on weekends. Furthermore, demand is subject to seasonal variations depending on climatic and cultural specifics, e.g. heating and lights in winter and air conditioning in summer. The detailed results of the study and deviation categories can be found in 5.3. The average duration of deviations is between 15 and 45 minutes around noon and between 30 and 90 minutes on evening on weekdays. On weekends, according to the shifted activity patterns, the average duration is between 15 and 90 minutes around noon and on the early afternoon, and between 15 and 60 minutes in the evening hours. Furthermore, numerous randomly occurring deviations below 5 minutes were detected. In regard to PV variations, studies show that 99 % last less than 20 minutes [83] [101]. Based on these findings, the short-term compensation algorithm is triggered in intervals of one minute.

Flexibilities

As the compensation of deviations is based on the evaluation of cluster flexibilities, they are updated on regular basis. Depending on the chosen implementation, the level of automation and communication possibilities, the responsibility for the update of the flexibilities could be taken by the heating system or the household, or by the aggregator agent. The heating system would consider the SoC of the thermal storage, its schedule, and the nominal power of the device and

communicate the provided flexibility to the aggregator agent. In case of limited automation, the aggregator agent could estimate the available flexibility of a group of households depending on the aggregated schedule, the number of residents, and the distribution of heating devices and thermal storage in the area.

As illustrated in figure 5.22, the flexibility limits of a heating system are defined by technical constraints and operational boundaries. In this figure the operation area of the heating device is defined by the temperature limits of the thermal storage. Common values for the temperature limits are around 20 °C–25 °C for the lower and 95 °C for the upper temperature limit. The operating point of the heating device is defined by the current temperature of the thermal storage. The trajectory of the operation point is described by the operating line, which represents the relation of generated thermal energy to the amount of generated electrical energy, also referred to as COP. The direction in which the operating point moves along its trajectory depends on the state of the device (on or off). The operating line and the current state of the device define its flexibility potential. For example, if the device has been working for several hours and is close to the upper temperature limit, it offers the flexibility to switch off and cover the warm water needs of the household from the almost fully charged thermal storage. It offers positive flexibility, as switching it off would decrease the distributed energy generation. In case the device is not running at the moment and stands around the middle of the operating line, the available flexibility is negative and around half of the flexibility for the fully charged thermal storage, as it could switch on and increase the distributed generation.

Based on this definition, the flexibility of a household is defined as follows:

$$FL_{\text{magn}N} = \{P_L, P_H \in \mathbb{R} \mid |P_L| \leq |P_H|, 0 \leq |P| \leq |P_{H\text{Smax}}|\} \quad (5.61)$$

$$FL_{\text{range}N} = \{t_L, t_H \in \mathbb{N} \mid t_L \leq t_H, 0 \leq t \leq 60\} \quad (5.62)$$

In Equation 5.61 and 5.62, $FL_{\text{range}N}$ and $FL_{\text{magn}N}$ are the time and power ranges of the flexibility of household N . $P_{H\text{Smax}}$ is the maximal amount of generation or consumption for a device from operational point of view. t_L and t_H , and P_L and P_H denote the lower and upper limits of the time and the power range of flexibility, respectively. As described in Equation 5.61, P could be less or equal to $P_{H\text{Smax}}$. Former is valid for the cases of non-scalable flexibility, meaning that the heating device can provide its full or none capacity, meaning it can be only switched on or off. In rare cases it is possible that the system offers flexibility less than $P_{H\text{Smax}}$, for example according to slow-charging settings for electric vehicles.

Positive flexibility $FL_{\text{magn}N}$ represents the capability of a household to increase their consumption, for example by switching on a HP, or to reduce their generation, by switching off a μCHP .

Power dispatch could be a range ($|P_L| \neq |P_H|$, e.g. in case of device capable of modulated operation), or a fixed value ($|P_L| = |P_H|$).

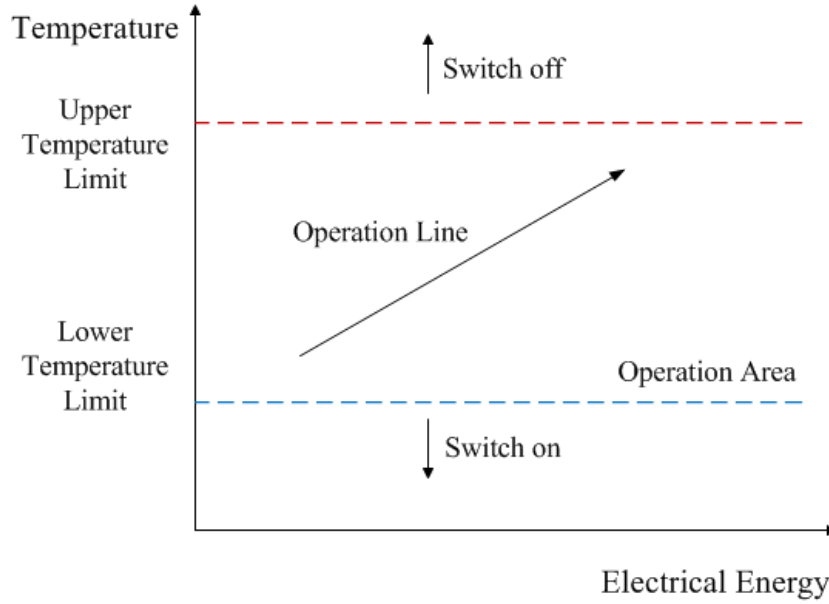


Figure 5.22: Flexibility of a μ CHP according to the operation area of the device

5.5.2 Coordinated Switching of Electro-Thermal Heating Systems

For the following description, it is assumed that the schedules from the planning phase are delivered in resolution of one hour and the coordination is triggered at the beginning of every hour.

To avoid simultaneous switching of the heating devices and the associated transient effects which could lead to grid instabilities, the order of switching the heating devices is set within the coordination phase. More sophisticated coordination concepts for the actuation are beyond the scope of this project. For the time non-critical applications such as switching of heating devices and charging of thermal storage the basic coordination method provides adequate performance. For the validation in simulation, the input from the households is created by generating a random number between 1 and 60, which is considered the switching minute for their heating device.

This approach is useful as a low-maintenance solution before a more sophisticated approach can be implemented and tested in the field test. The transient phase of the considered heating systems is in the range of 1–2 minutes. In case the switching of a heating system interferes with the switching point of another system, the household receives an alternative switching point such that there are no two devices switching at the same time. However, in clusters with limited number of HPs and μ CHPs interferences of the random switching points are not expected.

With increasing number of installed heating systems in the cluster, interferences of the switching

points will increase. At this point, the planned development of the heating systems as self-learning systems should include a scheme how to solve this problem.

Assuming the installation of more monitoring and advanced measurement devices in future, the development of a more sophisticated approach is possible. Smart meters should be able to sense the line and detect if there are transient effects, meaning for example that another device has just been switched. In this case, the device would back off and wait a certain time until it measures the voltage quality again and switches its device on as soon as there are no transient components in the voltage curve. This solution reduces communication cycles and traffic, but requires units capable of high-resolution measurements. This aspect is object of future investigation.

5.5.3 Compensation of Deviations

In the beginning of every hour, short-term weather forecasts are processed, in order to update the day-ahead forecasts for the generation from regional resources. Assuming that the higher share of renewables requires frequent short-term updates at the higher grid level too, the algorithm provides the distribution of lack or excess of energy from the higher to the lower grid level or among neighbor clusters within the coordination phase. However, following the aggregated schedule has higher priority for the cluster than signals from the upper grid level, they are only considered if the cluster detected or expects opposite deviations.

If deviations are detected which exceed the preset limits, adequate actions have to be taken for their compensation. There are several options to prioritize and to combine resources to deliver the dispatch energy.

The short-term compensation of deviations is illustrated by the example of a positive deviation. A positive deviation implying a higher energy demand than scheduled. In the following, the principle is explained schematically with the corresponding steps. First, a detected deviation is compared with the PV generation updates, assuming that a positive deviation would be directly compensated by PV generation higher than expected. The priority for switching of the heating devices follows the future minimal-consumption target. Therefore, in the second step devices are switched, which help to reduce energy consumption or to keep it low. For a positive deviation, this is a pool of HP, which is switched off according to the procedure described in section 5.5.3. The remaining deviation is tackled with the calculation of an optimal combination of μ CHPs according to the distance to the deviation cause.

The case of a negative deviation, meaning significantly lower energy demand than scheduled is targeted analogously, with opposite consideration of generation and consumption.

Prediction and Estimation of PV Generation

In the first step of the compensation algorithm, PV generation forecasts are compared with short-term forecasts in order to evaluate expected deviations and to consider them for the deviation calculation.

PV power generation is stochastic due to fluctuations, which depend on weather conditions like temperature, cloud coverage and humidity. Therefore, a reliable calculation of the PV generation is crucial for adequate planning and control actions during runtime.

The PV model comprises two aspects, simple semi-empirical relations to calculate the power output of the PV based on temperature and irradiation, and a more precise short-term prediction based on a linear regression model with a Kalman filter similar to [102].

The prediction of the power output of the PV is implemented as a series of calculations illustrated in 5.23.

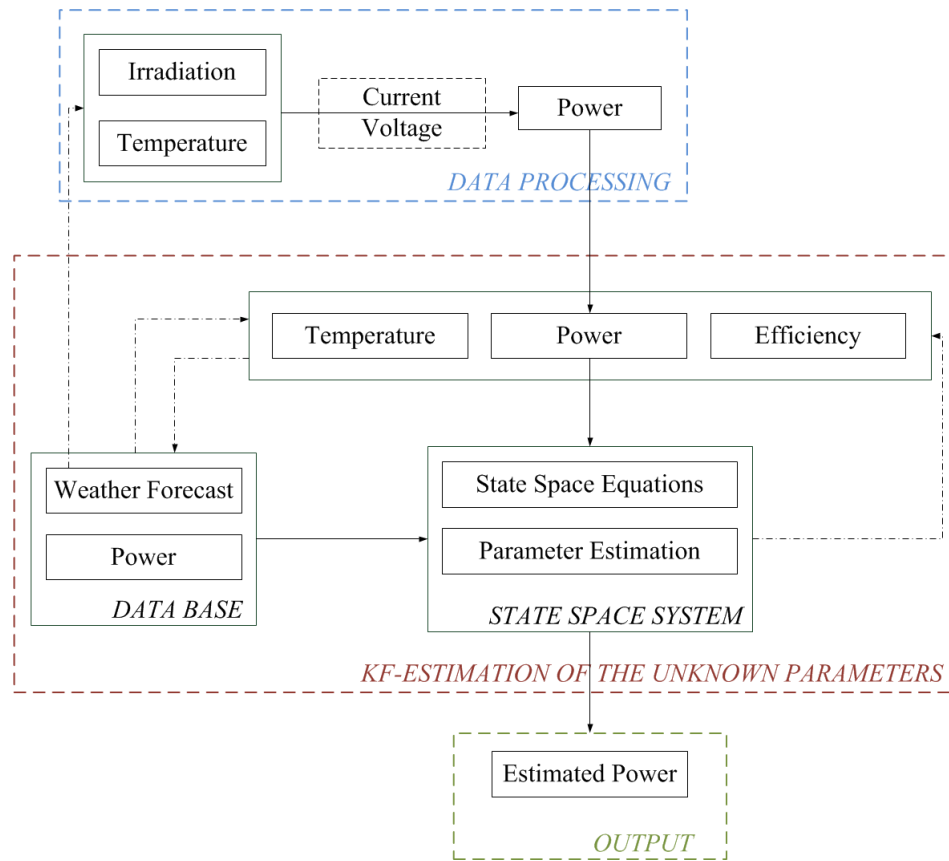


Figure 5.23: Estimation of the power output of a PV

The power generation of a PV system was modeled including quantities which influence the energy generation, such as temperature, irradiation, reverse saturation current, and the resulting efficiency factor. This basic model is presented as the data processing in the upper part of 5.23 and

marked with a blue dashed line. It was used to calculate an initial voltage-current curve, which is inserted into a regression model in order to increase the precision of the calculation (marked with xx line in 5.23). In the last step, a KF method is used to estimate modeling parameters and predict state transitions (marked as State Space System in 5.23).

Basic Model For this work, losses due to power electronics or other electrical components were neglected and only losses due to the internal resistance and current losses are considered. However, a significant factor for the performance of PV is the ambient temperature, which reduces the PV efficiency. As reference circumstances for PV generation is considered ambient temperature of 25 °C. According to [103], higher temperature reduces PV output as following:

$$I_{ph} = (I_{scr} + K\Delta T) \frac{G}{G_{ref}} \quad (5.63)$$

In Equation 5.63, I_{ph} is the internal current source equivalent of the PV and I_{scr} is the PV short-circuit current at the reference temperature. K represents a temperature coefficient [mA/ °C] which affects the saturation current, ΔT the deviation from the reference temperature, and G and G_{ref} are the present and the reference sun irradiation of 1000 W/m² [104].

Reverse saturation current according to the changes in ambient temperature is calculated as following:

$$I_s = I_{sr} \left(\frac{T}{T_{ref}} \right)^3 \exp \left[\frac{qE_g}{ak} \left(\frac{1}{T_{ref}} - \frac{1}{T} \right) \right] \quad (5.64)$$

where I_{sr} and I_s represent the reference and the present reverse saturation current, and T_{ref} and T the reference and present temperature. E_g is the energy band gap [eV], a is the ideality factor parameter of the PV model [eV], and k is the Boltzmann's constant.

The semi-empirical equations were used to calculate analytically an initial voltage-current curve, which is used in the estimation in order to improve the accuracy of the PV output power calculation.

Advanced Calculation The advanced PV calculation is based on a linear regression model with a Kalman Filter (KF) used to estimate the system states and to predict the power generation for the next time interval based on the last n intervals.

As a preliminary step for the calculation, the PV characteristics are considered according to the weather conditions. Weather conditions are categorized as sunny, cloudy and variably cloudy as in [101]. Assuming that a continuous cloud coverage results in lower irradiation without significant variations, only sunny and variably cloudy weather were considered. The PV characteristics

for cloudy weather are considered the same as for sunny weather with lower power generation. Pictures illustrate the power output for sunny and for variably cloudy weather.

In order to predict PV generation based on the semi-empirical equations, the PV efficiency is calculated for the current ambient temperature and irradiation, and the power output is calculated with the following regression model in Equation 5.65.

$$y_k = a_0 + \sum_{i=1}^n a_{k-i} y_{k-i} \frac{\eta_k}{\eta_{k-i}} + v_k \quad (5.65)$$

In Equation 5.65, y_k is the predicted value for the PV generation for time interval k , based on previous measurements from time intervals from 1 to n ; a_0 represents an error model; and η_k and v_k describe the efficiency and the measurement noise at time interval k .

In order to improve the prediction accuracy and to minimize errors due to unknown modeling parameters in the state-space representation of the system, a Kalman filter was implemented to predict the state transitions in the model based on measurements as illustrated in Figure 5.24.

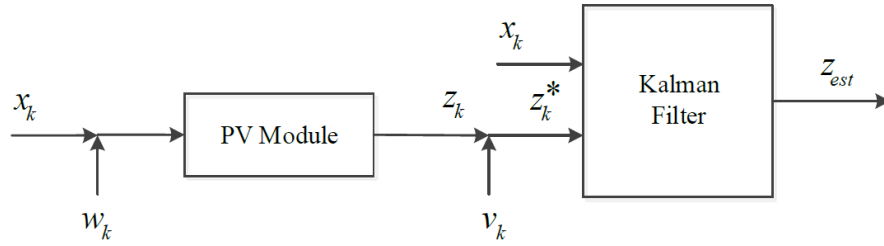


Figure 5.24: Scheme of the implemented Kalman filter

The parameter estimation is presented in Equations 5.66 – 5.71.

$$\hat{x}_{k+1|k} = A_{k+1} \hat{x}_{k|k} + v_{k+1} \quad (5.66)$$

$$P_{k+1|k} = A_{k+1} P_{k|k} A_{k+1}^T + Q_{k+1} \quad (5.67)$$

$$z_k = C_k \hat{x}_k + R_k \quad (5.68)$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k (z_k - C_k \hat{x}_{k|k-1}) \quad (5.69)$$

$$K_k = P_{k|k-1} C_k^T (C_k P_{k|k-1} C_k^T + R_k)^{-1} \quad (5.70)$$

$$P_{k|k} = (1 - K_k C_k) P_{k|k-1} \quad (5.71)$$

In Equation 5.66 $\hat{x}_{k+1|k}$ is the state estimation vector for the state transitions in the model. Propagation matrix A_{k+1} enables the state prediction for $k + 1$. P_k and P_{k+1} are the covariance matrices of the state estimation at times k and $k + 1$. Q_{k+1} is the normalized covariance matrix of the noise v_{k+1} . Equation 5.68 presents the employment of the measurements into the estimation with R_k being the normalized covariance matrix of the measurement error. The state transitions are updated according to Equation 5.69, where K_k is the KF gain defined by Equation 5.69. Equation 5.71 expresses the covariance update.

The detected deviation is updated according to the power output calculated for the PV. In case the PV update reduces the deviation into the predefined limits, the short-term compensation is considered successful and reset to the deviation detection state. Otherwise, the flexibilities offered by dispatch devices are considered. In the following, options for the combination of dispatch devices are presented.

Compensation of Deviations by Switching off HPs

Due to technical constraints and issues with the lifetime and the efficiency of the devices, heating systems cannot be switched at will. Technically, they can be switched up to 3–4 times per hour, however, manufacturers strongly recommend to keep the device state at least 5–6 hours. Beside the lifetime of the device, its efficiency is also highly increased if thermal storage is charged from low to full SoC in one cycle without interrupting the device. Therefore, the SoC of their thermal storage is an option for the choice of dispatch device. However, this approach is focused on the individual household and might not be conform to the cooperative strategy outline. Besides, we expect it to have long-term effects on the energy management algorithm, as it could lead to additional deviations.

Additional deviations can be avoided, if the choice of dispatch devices follows the scheduled demand curve as close as possible. This increases the overall stability of the algorithm, as addressing flexibilities has an impact on the operation parameters of the households and, therefore, on the demand profiles. For example, due to higher demand than scheduled, a μ CHP is addressed to switch on and generate energy. As the heating system is scheduled to be off and heat is currently not needed in the household, the thermal storage is being charged during the operation cycle. As soon as the thermal storage is fully charged, the μ CHP switches off and is blocked for a certain period of time according to the technical specifications. Accordingly, the heating device would cause an additional deviation in the time slot when it scheduled to switch on. In this way, the random use of flexibilities increases the level of uncertainty and the probability that closer to the schedule horizon, the allocation of flexibilities does not converge. On the other hand, this approach decreases

the aggregated flexibility in the cluster, as a certain amount of flexibility is blocked. An option is to keep the criterion dynamic and set a percentage limit for the acceptable deviation from the schedule. This could be for example $\pm 20\%$ for the deviation of the SoC from the scheduled value. This aspect of the short-term compensation algorithm will be a subject of further investigations.

Within 2DSM, grid aspects were considered a central concern and used as a criterion for the choice of dispatch resources. Grid aspects are at this point the minimization of losses in the system and the avoidance of congestions. Therefore, the criterion for the choice of dispatch resources is their physical distance from the cause of the deviation. The loss-minimization algorithm calculates the optimal combination of devices to deliver the dispatch energy, which is distributed inversely proportional to the distance to the source of the deviation. This strategy is interesting primarily for example for rural areas where distances between customers are high and there is significant voltage drop over the lines, but also for advanced billing models such as the option for a group of customers to install a near-district heating system and a combination of generation units and share the energy costs.

For the introduction of the short-term compensation concept we assume detected positive deviation from the schedule due to higher demand and the loss-minimization criterion for the prioritization of dispatch devices. Therefore, the compensation algorithm first addresses the energy consuming devices, in this case HP, which should be switched off as a zero-loss solution according to Mathieu et al. [105, 106].

Mathieu et al. describe a coordination method for the control of aggregations of thermostatically controlled loads (TCLs), such as refrigerators and HPs. The authors use Markov chain models to describe the temperature evolution of populations of TCLs and a Kalman filtering for state estimation in case of limited information from the system (see Figure 5.25). The authors offer different control options based on the computation of power from devices likely to switch on and off in the next time step due to environment and operational parameters, such as the outside temperature and the operation settings.

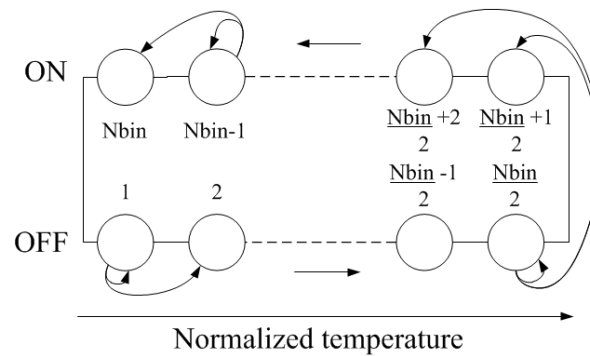


Figure 5.25: Markov chain model for the temperature evolution of populations of TCLs

Based on this work, a simplified state transition model for the HPs in the cluster was developed

for the short-term compensation approach based on a physical HP model. The state-space model aggregates the temperature bins from Figure 5.25 to the states on/off and satisfied/unsatisfied. For example, for the heating mode of a HP, the objective is to keep the temperature in the household within the predefined comfort area between 21 °C and 24 °C with a dead band of 1K. Room temperatures below 21 °C and above 24 °C mean that the device operates in unsatisfied mode. The moment when the room temperature exceeds 24 °C, the HP is in on and unsatisfied state. At 25 °C, the HP switches off. Due to the low ambient temperature, the room temperature would decrease; the system is in off and unsatisfied state as long the temperature is above 24 °C. Between 24 °C and 21 °C the HP is in off and satisfied mode. These state transitions are illustrated in Figure 5.26 for heating and for cooling mode.

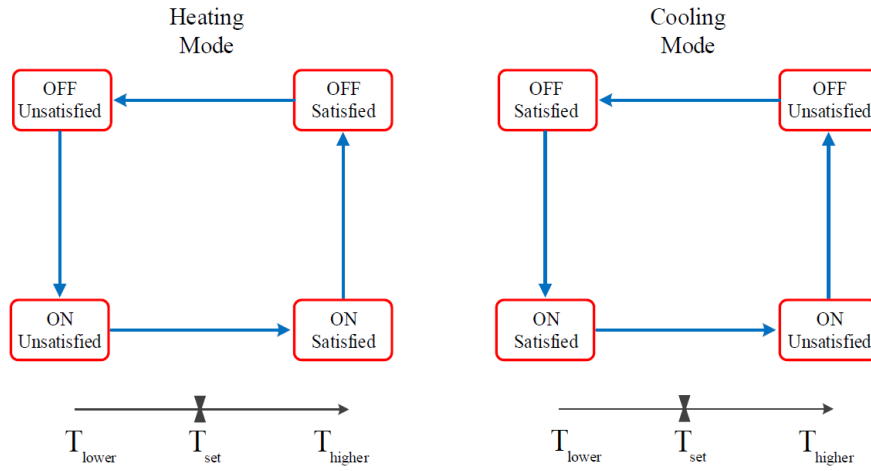


Figure 5.26: State transition model for the HP

To decrease the energy demand and to compensate the detected deviation, the total amount of power from HPs in the pool is computed, which are currently in an unsatisfied state. These are the devices with the highest probability to be switched in the next time interval. According to the magnitude of the deviation, the dispatch power provided by 5%, 10%, 15% and 20% of the best and good possible combinations is calculated in order to find best combination of devices.

In case the deviation could not be fully compensated with the HP pool, the flexibilities offered by μ CHPs are evaluated.

Compensation of Deviations by Switching on μ CHPs

As already mentioned, the choice of generation devices to deliver the dispatch energy follows a minimal-loss approach, based on the physical distance to the cause of the deviations [107]. In order to find the optimal combination of dispatch resources to compensate the detected deviations, the adequacy of a device is calculated considering its flexibility and, inverse proportionally, the

distance to the deviations. This principle is described by Equations 5.72 to 5.74, where loads are indicated with m , and distributed energy sources with n . In Equation 5.72, S_m^{sched} and S_m represent the scheduled and the actual consumption of node m . As the project area is purely residential, reactive power is not considered at this point. Accordingly, a deviation from the schedule at node m due to higher demand is indicated with ΔP_m . In Equation 5.73, the flexibility of the heating device at node n is calculated as the difference between the maximal and the current power generation. Based on that, in Equation 5.74 the contribution P_m^n of node n is calculated according to its distance to the deviation d_m^n and its flexibility P_n^{flex} .

$$\Delta S_m = S_m - S_m^{\text{sched}} = \Delta P_m + j\Delta Q_m \quad (5.72)$$

$$P_n^{\text{flex}} = P_n^{\text{max}} - P_n \quad (5.73)$$

$$P_m^n = \Delta P_m \frac{P_n^{\text{flex}}}{d_m^n} \left(\sum_{n=1}^N \frac{P_n^{\text{flex}}}{d_m^n} \right) \quad (5.74)$$

The consideration of the distance to the deviation cause for all distributed energy sources enables the calculation of an optimal dispatch solution for the compensation of the deviation.

In the case of a positive deviation due to higher demand, the method is applied for the energy generation resources, which offer flexibility in the considered time slot. For a negative deviation, the same method is applied for the energy consuming heating systems.

In the last step of the compensation algorithm, remaining deviations are evaluated and offered to neighborhood clusters or to the upper grid level.

5.5.4 Case Study

Here, results from the short-term compensation are presented on the example of a radial grid segment from the model region. In order to illustrate the principle of the short-term compensation algorithm, two scenarios are studied for a realistic deviation vector, according to the categories in section 5.3. The first scenario, based on a grid segment in the project area, demonstrates the compensation steps and explains the way decisions are taken. The second scenario contains 146 households and demonstrates the different criteria for the assignment of dispatch resources for the compensation of deviations.

Basic Scenario

First, in order to demonstrate the basic principle of the compensation approach, an exemplary constellation of 19 buildings in one street is studied as presented in Figure 5.27. The grid segment

maps a part of the model region. The modeled buildings and the grid characteristics reflect the real circumstances in the area. The tests are focused on the potential for compensation of deviations at local level.

In Figure 5.27, the dispatch resources are illustrated as an additional load or generation source at the corresponding node. All nodes correspond to buildings in the project area. There are single and double dwellings, and apartment buildings with several households, 62 households in total, with up to five residents.

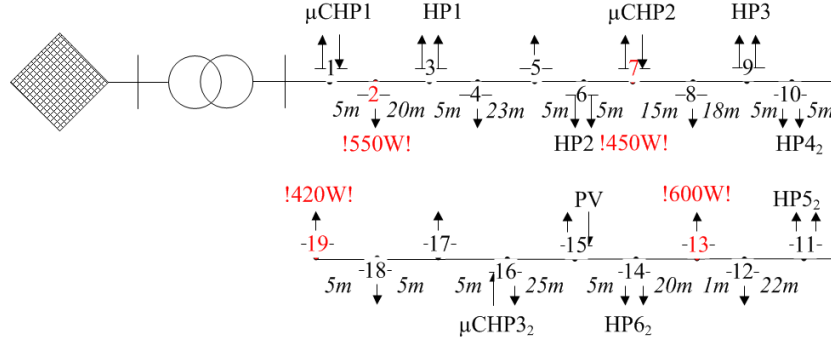


Figure 5.27: Grid segment for the basic scenario of the case study

In order to generate a realistic deviation vector, the findings from the study on deviations were applied (see 5.2). According to the frequency of occurrence of deviations, following deviations were implemented:

Node 2, a 5-person household: deviation with a magnitude of 550W and duration of 30 minutes

Node 7, a 4-person household: deviation with a magnitude of 450W and duration of 35 minutes

Node 13, a 5-person household: deviation with a magnitude of 600W and duration of 40 minutes

Node 19, a 3-person household: deviation with a magnitude of 420W and duration of 45 minutes.

For the test scenario, dispatchable loads (HP) are modeled at nodes 3, 6 and 9, and dispatchable generation (μ CHPs) at nodes 1 and 7. The schedules, SoC, and flexibility for the time interval 10 a.m. – 1 p.m. are listed in Table 5.7. The scheduled operation mode (schedule) is 0 for devices which are scheduled to be off this hour, 1 for dispatchable loads, and -1 for dispatchable generation sources. As described in 5.5.1, positive flexibility power range denotes the flexibility of the household to increase its demand. For example, according to the schedule for the time 12 p.m. – 1 p.m., the thermal storage of HP1 is charged to 49 % in the beginning of the interval. HP1 is scheduled to be operating during this time, and offers negative flexibility of 400W ($FL_{\text{magN}} = -0.4\text{kW}$) at

Table 5.7: Schedules and flexibilities for the resources in the case study

Time Slot	Parameters	HP1	HP2	HP3	CHP1	CHP2
10a.m.–11a.m.	Schedule	1	0	0	-1	-1
	SoC	37 %	35 %	70 %	46 %	55 %
	FL_{range}	{0, 60}	{0, 60}	{0, 60}	{0, 60}	{0, 60}
	FL_{magnN}	{-0.4}	{1.0, 5.0}	{1.0, 3.0}	{-0.37}	{-0.54}
11a.m.–12p.m.	Schedule	1	1	0	-1	-1
	SoC	43 %	30 %	69 %	53 %	64 %
	FL_{range}	{0, 60}	{0, 60}	{0, 60}	{0, 60}	{0, 60}
	FL_{magnN}	{-0.4}	{0}	{1.0, 3.0}	{-0.37}	{-0.54}
12p.m.–13p.m.	Schedule	1	1	0	-1	-1
	SoC	49 %	41 %	68 %	60 %	73 %
	FL_{range}	{0, 60}	{0, 60}	{0, 60}	{0, 60}	{0, 60}
	FL_{magnN}	{-0.4}	{0}	{1.0, 3.0}	{-0.37}	{-0.54}

any time ($FL_{\text{rangeN}} = 0.60 \text{ min}$). Further negative flexibility is offered by μCHP1 and μCHP2 , which could increase their generation by 370 W and 540 W.

Coordination

In the first time slot from 10 a.m. to 11 a.m., HP2 is scheduled to be off. Due to the decreasing SoC of the thermal storage (30 %), it is scheduled to switch on in the interval between 11 a.m. and 12 p.m. The device generates a random number for its switching time and sends the signal to the system. The short-term PV forecast updates indicate expected generation increase by 400 W over 40 minutes.

Processing and Compensation

The deviations are depicted in Figure 5.28 according to their location as described above. The increased PV generation reduces the deviation magnitude from 2020 W to 1620 W. After switching HP1 off, the deviation is increased to 1220 W.

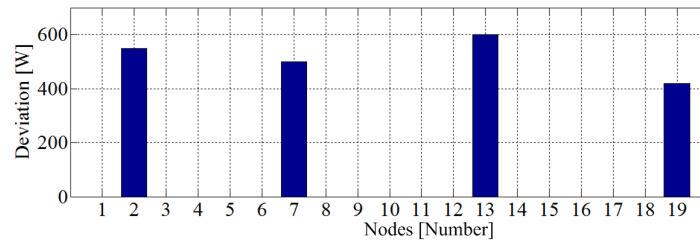
**Figure 5.28:** Deviations in the time 11.15 a.m.–11.50 a.m.

Figure 5.29 illustrates the distances between the μ CHPs and the nodes in the grid segment. Furthermore, Figure 5.29 shows the optimal combination of generation sources for the compensation of the occurred deviations according to Equation 5.74. For the deviation of 550W at node 2, the most efficient option is to address μ CHP1, due to the short distance of 5m between these nodes. The adequacy of μ CHP1 decreases with increasing distance to the other deviations at nodes 3, 7 and 19.

Same is valid for μ CHP2. As there is a deviation at the same node, the most efficient solution is to assign this resource to compensate the deviation.

In the basic scenario with only 19 nodes and four deviations, the optimal combination of devices is obvious. However, in large areas with several hundred nodes and distributed resources and, accordingly, frequent deviations, the approach delivers explicit results which enable the implementation of further prioritization criteria such as the SoC.

By using the offered flexibility of both μ CHPs, the deviation is reduced to 310W. Depending on the set limits, the deviation residual can be neglected or communicated with neighbor clusters as described above.

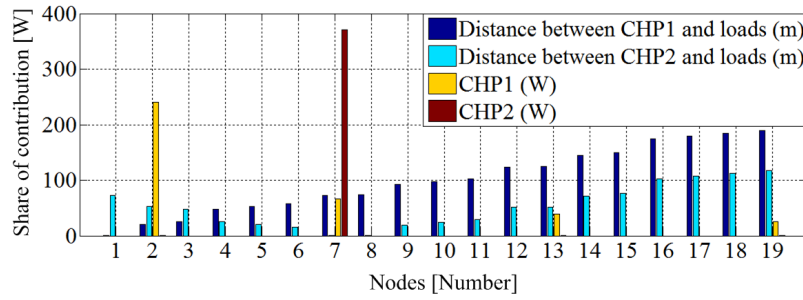


Figure 5.29: Distance to the loads and corresponding adequacy for compensation of the deviations in the basic scenario

Advanced Scenario

Here, the performance of the compensation algorithm and its interaction with the scheduling phase are illustrated on a scenario with 146 nodes, several HPs and 5 μ CHPs. The nominal thermal generation power of the μ CHPs is 7kW while the nominal electrical power is 3.08kW.

Figure 5.30 shows the deviation distribution, again calculated according to the deviation study. The aggregated deviation of 7.94 kW could be compensated by one of the three μ CHPs, which provide flexibility in the considered time interval. For the prioritization of one μ CHP which should be addressed, first the losses are evaluated according to the approach described in 5.5.3.

The minimum-loss solution is shown in Figure 5.31, where the adequacy of the four dispatch resources are illustrated next to the deviations. Obviously, the optimal combination from this point

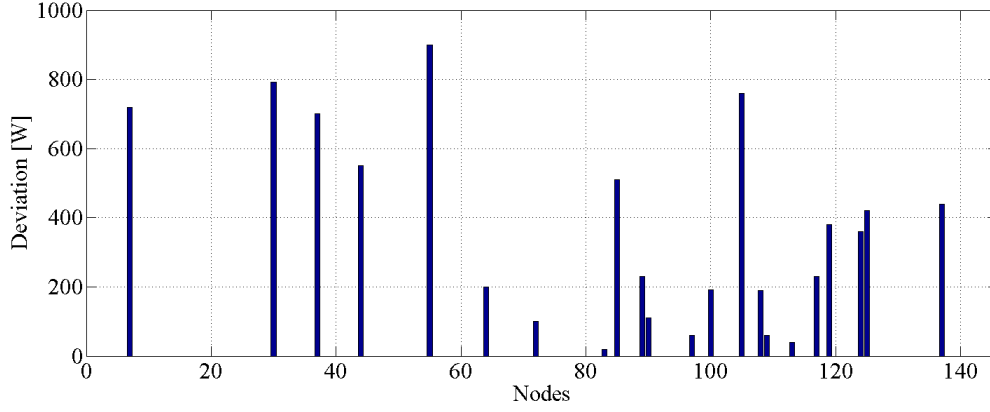


Figure 5.30: Deviations in the advanced scenario with 146 households

of view are the μ CHPs 1 and 2.

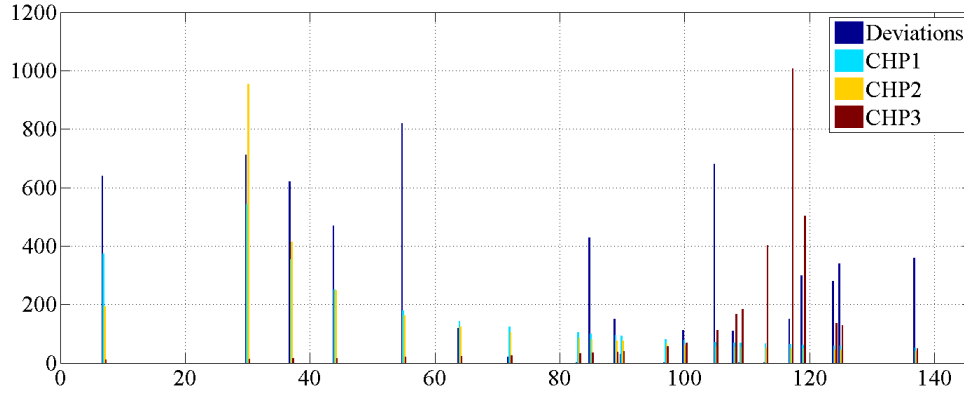


Figure 5.31: Deviations and adequacy of the resources for their compensation

A different view is obtained applying the other criterion, this is the limitation on deviations from the scheduled SoC. Here, the more suitable resources are μ CHP2 and μ CHP3. The scheduled SoC of the thermal storage of μ CHP1 is 0.43, and the actual SoC is 0.55, this is a deviation of 12 %. On the other hand, μ CHP3 is little behind its schedule of 0.72. The actual SoC of CHP3 is 69 %. By switching μ CHP3, the discrepancy would be compensated and the effects of the short-term compensation on the schedules would be decreased. The decision is a matter of priorities which could be set dynamically, depending on the state of the grid and the overall discrepancy with the schedules.

6 Conclusion

Within the 2DSM project a new concept of holistic energy management for city districts was introduced and developed. In order to develop, test and present the viability of the new approach a simulation platform for multi-energy systems was developed and implemented. The presented platform allows for simulating and analyzing large scale city district energy systems comprising a large number of individual buildings and BES, energy supply infrastructure and system level energy management and control algorithms. The approach of the simulation platform is to couple already existing simulation tools and models which enables a professional application. The applied paradigm of parallel computing provides a good performance regarding the computation time. The modularity of the simulation platform allows to configure it according to the requirements of further projects.

One of the most important components for the 2DSM approach are energy storages, which allow electricity coupled supply systems like HP or CHP to decouple electricity consumption or respectively generation from the local thermal demand. Within this project we have analyzed the feasibility and the cost efficiency of different energy storage approaches, finding that thermal storage is and will be the most suitable and cost efficient technology for that purpose. While it is technically possible to utilize also electrical or chemical storages for residential DSM, they turn out to be by far more expensive. Furthermore, the possibility to utilize the thermal mass of the building itself as a storage was analyzed. Promising results were found, indicating that a well chosen configuration of building type, supply system and energy management can potentially allow considerable storage capacity in the buildings thermal mass without violating residents' comfort conditions. Among others, heating systems directly coupled with the buildings thermal mass (e.g. under floor heating or concrete core activation) and a good insulation standard are important factors for efficient energy storage within the building's mass. Once suitable supply systems and a communication infrastructure is in place such an energy storage approach does not induce further cost.

Additionally, to facilitate conception and simulation of such interdependent energy management approaches like 2DSM in the future CDIM, an integrated data management concept for city districts, was introduced. Simulations based on different input data sets were performed to examine the impact of data availability and quality and show exemplary benefits of the availability of a CDIM. It is shown, that if incomplete or missing building information has to be estimated, even small deviations to the actual values can considerably change the simulation results. Especially for new or refurbished buildings insulation standards and supply systems are hard to estimate, leading to large discrepancies in the simulated energy demand and corresponding energy costs.

Furthermore, it was found that city district data allows creating more efficient local energy management scenarios. Since such data can influence the choice of supply systems and energy sources, the resulting energy cost and primary energy demand can be strongly influenced. Particularly, the conception of local micro district heating infrastructures and the integration of local renewable energy sources can distinctly impact the simulation results. Thereby, the simulation results revealed differences of up to 57 % in primary energy demand between fair data estimation and the CDIM scenario.

Two approaches for the scheduling of distributed energy conversion units within a microgrid have been formulated. A central strategy in which an aggregator agent performs solely the coordination in the microgrid while receiving several data from the participants i.e. the electrical consumption data, characteristics of the heat supply units and thermal demand forecasts. The results show that the coordination level is quite high allowing for a near energy independent performance of the microgrid. However, it can be foreseen that privacy issues arise with the implementation of such an approach. The second scheme is based on a decentralized coordination strategy in which the house agents locally compute the schedule in form of demand side response to a price steering signal. This signal is determined based on the availability of renewable energy sources as well as the interaction of the different participants e.g. CHPs and HPs in the microgrid. The bottom level optimization enhances the scalability character of this solution. Yet, the results indicate a lower coordination level mainly due the high generation of the CHP units. This aspect must be investigated in further studies.

In order to compensate deviations from the schedules due to short-term forecast updates and human behavior, a short-term compensation algorithm has been developed and implemented. The algorithm is organized in a pre-phase, where once an hour the switching devices are coordinated, and compensation phase, which is triggered as soon as the detected deviations exceed the preset limit. The compensation algorithm allows the choice of criteria to find the optimal combination of dispatch devices, e.g. grid losses or the state of charge of the thermal storage. The test results confirm the feasibility of the compensation algorithm, however, a compromise has to be found between grid aspects, customers' financial damage, and the compliance of the agreed schedules.

7 Further Steps

A proof of concept of a co-simulation platform for city districts has been developed and implemented. Further development is needed for

1. the automation of the scenario setup,
2. the implementation of data storage in a relational database (PostgreSQL),
3. the integration or development of data analysis tools for demand side management and multi agent systems,
4. the development of an integrated tool-chain for data collection, scenario selection, simulation and data analysis,
5. the integration of further solvers and solver interfaces which allow a better model exchange and integration like FMI
6. the implementation of additional simulation models to consider in a scenario and
7. the integration of local heating networks models into the co-simulation platform to allow for a multi-grid analysis. The availability of a local heating network supplied by decentralized energy conversion unit, provides additional thermal flexibility that can be used to adapt to the fluctuating renewable generation. This is currently under investigation based on an internal study [108].

Furthermore, several approaches for demand side control i.e. central and decentral, have been tested in 2DSM. The decentral coordination based on a scalable, flexible and extendable multi-agent system is identified as the most promising approach. Further research and development of energy management algorithms is needed to enhance the coordination degree of this solution. Thereby, the development in the energy economy must be pursued, analyzed and incorporated in the formulation of the demand side management strategies. Further, the architecture of the multi-agent system presented in this work was kept general. The development of a business case would require a mapping onto actual stakeholder.

Moreover, future investigations are needed to analyze the technical implementation of this system. This includes testing of the performance and fault tolerance as well as the communication infrastructure. Additionally, an implementation on hardware devices is needed to pave the way for real life application.

The test results confirm the feasibility of the short-term compensation algorithm, however, several aspects have to be further investigated. The developed criteria for the choice of dispatch resources

for the compensation of the deviations have to be evaluated and weighted against each other in order to develop adequate algorithms for their combination. Furthermore, the influence of these criteria on the grid, the customers' financial damage and on the compliance of the agreed schedules have to be studied profoundly.

Thermal storage capacity is a core element within the dual demand side management approach. IT has proven to be cost efficient and very well suitable for the 2DSM approach. For classical hot water storage tanks further analysis has to focus on the required sizing, insulation and operation strategy for different building types. Furthermore, possible benefits for the domestic energy management through parallel operation of thermal storage with other storage technologies (e.g. batteries) should be analyzed. This analysis also indicated considerable potential for thermal energy storage in the thermal building mass, as well as the suitability of our simulative approach to investigate this process. Building on the first promising results, analysis will be extended to a portfolio of different building structures and heating technologies. Further DSM algorithms using the buildings mass will be developed and the residents thermal comfort for the resulting conditions will be evaluated.

8 Literature

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9.3 Nomenclature

Symbols and Units

Symbol	Description	Unit
a	ideality factor parameter	—
a_0	Error model	—
A	Area	m^2
A	Propagation matrix	—
b	Linear trend component in Holt-Winters models	—
c	Economic cost in optimization problems	€
c_p	Specific heat capacity at constant pressure	$\text{J}/(\text{kgK})$
C	Heat capacity	W/kg
d	Seasonal component in Holt-Winters models	—
d	deviation	W
e	Forecast error	W
E	Energy	J
G	Irradiation	W/m^2
I	Direct solar irradiation	W/m^2
I	Electrical current	A
k	Boltzmann's constant	J/K
K	Degree of coordination	W^2
K	Kalman filter gain	—
l	Level component in Holt-Winters models	—
L	Heat conduction coefficient	$\text{W}/(\text{m}^2 \text{K})$
M	Upper boundary	—
p	Economic profit in optimization problems	€
P	Electrical power	W
P	Flexibility	W
$\dot{Q}$	Heat flow	W
r	Economic revenue in optimization problems	€
t	Time or time step	s
T	Thermodynamic temperature	K
U	Inner energy	J
V	Volume	m^3
$\dot{V}$	Volume flow rate	m^3/s

Continuation on the next page

Symbols and Units

Symbol	Description	Unit
y	predicted value of PV generation	W

Greek Symbols

Symbol	Description	Unit
η	Efficiency	—
ϕ	Smoothing parameter in Holt-Winters models, $0 \leq \phi \leq 1$	—
ω	Smoothing parameter in Holt-Winters models, $0 \leq \omega \leq 1$	—
v	measurement noise	W

Indices and Abbreviations

Symbol	Description
2DSM	Dual Demand Side Management
AA-CEAS	Advanced-adiabatic Compressed Air Energy Storage
APC	Automatic Process Control
ANN	Artificial neural network
BCVTB	Building Controls Virtual Test Bed
BES	Building Energy System
BIM	Building Information Model
CAES	Compressed Air Energy Storage
CCA	Concrete Core Activation
CDIM	City District Information Model
CHP	Combined Heat and Power
CL	Center Line
COP	Coefficient of Performance
DLL	Dynamic Link Library
DR	Demand Response
DMS	Distribution Management System

Continuation on the next page

Indices and Abbreviations

Symbol	Description
DSM	Demand Side Management
DSO	Distribution System Operator
EEG	German Renewable Energy Ordinance
EEX	European Energy Exchange
EH	Electrical heater
el	Electricity
EL	Entity Layer
EnEV	German Energy Saving Ordinance
ESI	Energy Service Interface
est	estimation
EWMA	Exponentially Weighted Moving Average
g	band gap
GB	Gas Boiler
GIS	Geo Information System
HDC	Heat Demand Curve
HP	Heat Pump
HS	Heating System
IPC	Inter-process communication
k	time interval
KF	Kalman Filter
LCL	Lower Control Limit
LCOE	Levelized Cost of Energy
m	loads
magnN	Flexibility magnitude
max	Maximal
min	Minimal
MTS	Macro Time Step
μ CHP	Micro Combined Heat and Power
μ TS	Micro Time Step
MAS	Multi-Agent System
MASE	Mean Average Scaled Error
MIP	Mixed integer linear program
n	distributed energy sources

Continuation on the next page

Indices and Abbreviations

Symbol	Description
NARX	Nonlinear AutorRegressive eXogenous
NAS	Natrium-Sulfur Battery
NL	Network layer
OS	Operating System
P2G	Power-to-Gas
PCC	Point of Common Coupling
PEF	Parallel Execution Framework
ph	internal current source equivalent of the PV
PHS	Pumped Hydroelectric Storage
PV	Photovoltaics
rangeN	Time range of the flexibility
RE	Renewable Energies
ref	reference
RTI	Runtime Infrastructure
s	present reverse saturation current
sr	reference reverse saturation current
SA	Separation Algorithm
SCL	System Control Layer
set	setpoint
SHS	Sensible Heat Storage
SLP	Standard Load Profile
SoC	State of charge (energy storage)
SPC	Statistical Process Control
SSE	Sum of Squared Error
TCL	Thermostatically Controlled Load
TMY	Typical Meteorological Year
TRY	Test Reference Year
UCL	Upper Control Limit
VRB	Vanadium Redox Battery
VSV	very-short voltage variations

9.4 Publications

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9.6 Project Timeline

	1 st Year 1. June 2011 – 31. May 2012				2 nd Year 1. June 2012 – 31. May 2013				3 rd Year 1. June 2013 – 31. May 2014			
WP 1												
WP 2												
<i>WP 2a</i>												
<i>WP 2b</i>												
WP 3												
WP 4												
Documentation												

WP 1: Analysis of the influence of decentralized power generation on the local city environment and collection of city district modeling data.

WP 2: Modeling and simulation of existing grids and city district thermal demand.

WP 2a: Modeling of thermal zones, heating systems, electrical grid and occupancy profiles.

WP 2b: Development of simulator platform (MESCOS) and integration of tools and their communication.

WP 3: Development of Dual Demand Side Management intelligence. Central and decentral approach.

WP 4: Development of the city district information model.

9.7 Activities within the Scope of the Project

Knowledge gained in this project has already been used in other projects in the field of demand side management. During this project several publications in different conferences and journals have been written. Based on the current research new projects in the field of demand side management and smart cities are derived and proposed.

Project synopsis

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Categories E.ON ERC focus:

- | | |
|---|---|
| ☒ Small Scale CHP | ☐ Large Power Plants |
| ☒ Energy Storage | ☒ Energy Efficiency |
| ☐ Consumer Behavior | ☐ Energy Economics Modeling |
| ☒ Energy and Buildings | ☐ Power Electronics |
| ☒ Distribution Networks | ☒ Renewable Energy |
| ☐ Carbon Storage (CCS) | ☐ Others: Medium-Size Power Plants |

Type of project report: Final Project Report

Start and end date of project: June 2011 – May 2014

Project in planned timelines: ☒ yes ☐ no (see section 9.6)

Participating Chairs of E.ON ERC

- ☒ Automation of Complex Power Systems (ACS)
- ☒ Energy Efficient Buildings and Indoor Climate (EBC)
- ☐ Future Energy Consumer Needs and Behavior (FCN)
- ☐ Applied Geophysics and Geothermal Energy (GGE)
- ☐ Power Generation and Storage Systems (PGS)

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